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Deaths of Despair in the United States

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DEATHS OF DESPAIR IN THE UNITED STATES

by

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ABSTRACT

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by

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Utah State University, 2021

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Thanks to medical advancements, life expectancy has substantially increased in the twentieth century, particularly in advanced nations. However, the life expectancy of Americans has become stagnant since 2010; that is unexpected news and a warning. An important body of scholarship has attempted to explain stagnant longevity in the United States through “deaths of despair”. According to the theory, there is a rise in midlife mortality among non-Hispanic white Americans, especially without college education, that is attributable to drugs, alcohol, and suicide. Although numerous studies have inspected various aspects of that thesis, there are still significant unresolved questions.

This dissertation addresses two major gaps in the extant literature. First, focusing on geographic disparities, this study analyzes trends in deaths of despair for each of the 50 states from 1999 to 2019. Although the results show an overall uptrend in the US for all three contributors to deaths of despair, there are large disparities among states with respect to rates of increase. For example, New Jersey, North Dakota, and Maryland have the highest drug mortality growth among midlife whites, with annual change in each state near 20 percent; conversely, Hawaii, Wyoming, and

Utah have the lowest growth in recent years, with annual percent change around zero. In general, states such as Maryland, Connecticut, New Jersey, Delaware, and New Hampshire, all located in the Northeast region, are experiencing the highest growth in despair mortality in recent years.

The second literature gap is an insufficient explanation for deaths of despair; consequently, this dissertation explores a large set of social and economic variables. This study applies spatial fixed-effect panel models to examine how changes in predictor measures for each county are associated with despair-related mortality. The findings suggest increases in factors such as social capital, percentage of married people, and population density in the county lead to lower despair-related mortality over time; by contrast, rising rates of poverty lead to higher despair-related mortality. In addition, the findings highlight the importance of precieved loss of socioeconomic status (e.g. average levels of education, income, and employment) at the county level for midlife whites.

(157 pages)

PUBLIC ABSTRACT

Deaths of Despair in the United States

Amin Etemadifar

Life expectancy is one of the most important indicators of public health and is an indication of overall health status in a population. Thanks to public health and medical advancements over recent decades, the life expectancy of all nations has significantly increased, and that is more true for developed nations like the United States. However, the most recent data shows the longevity of Americans has become stagnant since 2010. So the first question that comes to mind is why that is happening, and the main goal of this dissertation is to answer that question.

In order to address that question, this study examines a theory called "deaths of despair". According to that theory, the mortality of midlife white Americans, especially those without college education, has significantly increased over recent decades and that is one of the major reasons of life expectancy stagnancy. Specifically, the theory points to three causes for deaths of despair, including drugs, alcohol, and suicide; However, those causes are the result of underlying problems that have a root in the social and economic determinants of health. The findings of this dissertation have two parts. The first part explores the geographic distribution of midlife white mortality, showing how each cause of death (i.e. drug, alcohol, and suicide) differs across US states. For example, while drug mortality is a critical issue in West Virginia, that is not the case in Utah, but in Utah suicide is a major problem.

The second part of the findings deals with an explanation for deaths of despair at the county level, and examines the influence of different social and economic factors on despair mortality. The findings suggest social isolation and economic hardship as two significant determinants of deaths of despair. In addition, a perceived loss of socioeconomic status (defined by factors like income, education, and employment) for white people may be another significant factor. One important conclusion is that there is a subgroup of the non-Hispanic white American population that is struggling with life difficulties as much as other marginalized groups, and they need special attention and support.

DEDICATION

I dedicate this dissertation to Vivian, for all of the valuables things that she taught me, and for all of those great memories from the mountains of Utah to the beaches of California. She remains in my heart forever.

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CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER I

INTRODUCTION

Statement of problem

Thanks to health improvements and medical advancements, life expectancy increased dramatically in the twentieth century, especially in developed nations. For generations, Americans have become used to an annual increase in life expectancy and each new generation has expected to live longer than its parents. We can see this hopeful expectation in a speech that Francis Collins, the Director of National Institutes of Health (NIH), presented in 2014: “our Nation has gained about one year of longevity every six years since 1990. A child born today can look forward to an average lifespan of about 78 years — nearly three decades longer than a baby born in 1900” (NIH 2015).

However, according to the latest data from the National Center for Health Statistics (NCHS), the life expectancy of Americans has been stagnant in recent years. For example, in 2010 U.S. life expectancy was 78.7 years, the same value as in 2018. As figure 1 presents, there was an upward trend in life expectancy from 1999 to 2010, but after 2010 that measure fluctuates around 78.7. In some years (e.g. 2017) there is even a decline in life expectancy. Evidence over the past decade suggests a long-term stagnation in U.S. life expectancy, which is surprising and troubling news. The last time that the United States experienced a decline in life expectancy for multiple years was 1918, during the first world war and the Spanish influenza pandemic (Newman 2018). The current stagnation in life expectancy is a serious

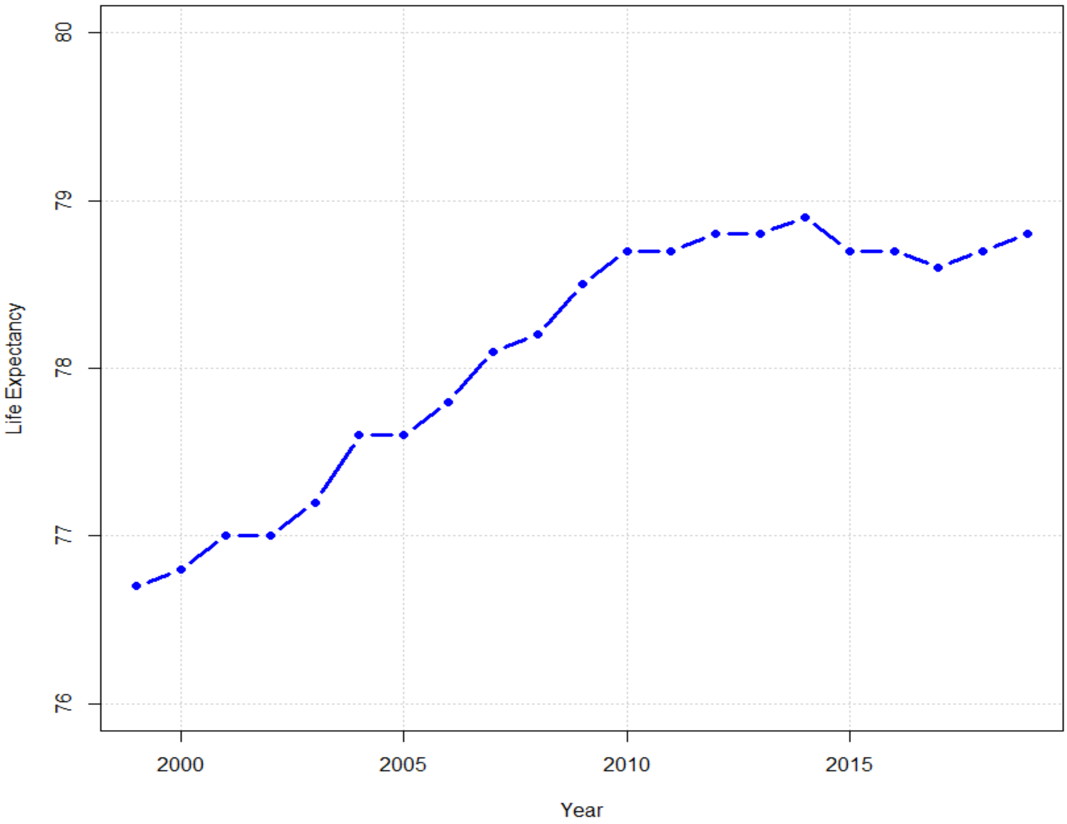


Figure 1. Life expectancy in the United States of America, 1999-2019 (NCHS 2021)

warning to the U.S. public as well as policymakers and public health authorities. The theory of deaths of despair provides one major explainaton for that problem.

Deaths of despair (DoD) theory

Prior to 2015, some studies warned about the future life expectancy of Americans. For example, Olshansky (2005) refers to the rise of obesity since the 1980s and concludes that we may expect a decline in life expectancy in the near future. Reither et al. (2011) assert that conventional demographic and statistical measures, such as period life expectancy, can create inaccurate impressions about current and future population health status. Other measures and projection methods that incorporate the health of younger birth cohorts suggest that U.S. death rates are likely to increase in the future. Since the publication of these articles, life expectancy has indeed stagnated and declined—but the reasons why are contested among scholars in this field of study.

Denney et al. (2013) highlight stagnant life expectancy among Americans and the continuing drop of the U.S. in international life expectancy rankings. By conducting an analysis of more than 70 years of mortality data, they project that U.S. life expectancy in 2055 will increase by only three additional years, relative to current levels. Avendano and Kawachi (2014) attempt to answer why longevity among Americans is the lowest among other high-income countries. They emphasize contributors to suboptimal longevity such as socioeconomic inequalities, differences in health care, and individual behaviors as the main causes of that difference.

After Deaton and Case (2015) published their seminal study on "deaths of despair," attention to the issue of U.S. life expectancy significantly increased in both academic journals and non-academic media. By examining data from 1999 to 2013 and presenting the results in their article "Rising morbidity and mortality in midlife among white non-Hispanic Americans in the 21st century," Deaton and Case (2015) point to an unexpected increase in the mortality of middle-aged non-Hispanic white Americans in recent years. They argue the United States is the only country among high-income developed countries experiencing such an increase in mortality among people in midlife. For example, from 1978 to 1998, the death rate of 45 to 54 year-old people in the U.S. decreased by 2 percent per year, similar to other industrialized countries. However, after 1998, the death rate of that age group started to increase by 0.5 percent per year in the U.S. and since then has significantly diverged from other developed nations.

In addition, the authors assert that the mortality increase is happening among non-Hispanic white people, not other racial and ethnic groups in the U.S. population. They suggest two explanations for the matter. First, they highlight three causes of death including drug poisoning, suicide, and chronic liver diseases and cirrhosis (mainly caused by alcohol abuse) as the most important culprits of mortality increase among midlife white Americans. They assert that the increase in suicide and drug- and alcohol-related mortality is enough to offset the decrease in mortality caused by other major causes of death like cardiovascular diseases and cancers (Case and Deaton 2015, 2017). The second explanation is related to distal determinants of health involving social, economic, and cultural factors. They argue that education is a critical determinant of death rates as, between 1999 and 2013, the death rate increased by 134 (per 100,000 persons) among midlife white Americans without a college education. Over this same period, midlife white Americans with some college education experienced a decline in mortality of 3.3 deaths per 100,000 persons, and midlife white Americans with a Bachelor's degree or higher experienced a decline of 57.0 deaths per 100,000. In addition, Case and Deaton (2015) point to increasing income inequality and economic decline after the 1970s as major contributors to increasing mortality rates among midlife white Americans. Because of those factors, many midlife working-class baby boomers with lower education have found that they are not able to exceed the living standards of their parents. As a result of poor economic prospects and the lack of well-paying jobs, that cohort of the population feels pain and distress in their lives such that they gravitate toward self-harm and drug abuse. The authors refer to this phenomenon as "deaths of despair."

In a more recent study, Case and Deaton (2017) contend that deaths of despair actually started to rise in the early 1990s, but the decrease in some major causes of deaths, like cardiovascular diseases, offset that increase. However, while deaths of despair continued to rise after 1999, the decline in other major causes of death like heart disease leveled off and did not offset deaths of despair anymore. In the study, they refer to “cumulative disadvantages” as the main mechanism driving the problem (i.e., DoD). By cumulative disadvantages, they mean social, cultural, and economic changes in American society after the 1970s. From that time, the heyday of working-class wages ended and the traditional structure of economy and society that once supported working-class people began to falter. For instance, unlike previous generations, today’s workers cannot expect a well-paying manufacturing job. As a result of globalization and technical advancements, the quantity and quality of well-paying jobs for the working-class have declined and labor unions have lost their importance. At the same time, marriage, the traditional institution to provide personal and familial support, is no longer the only way of partnership and raising children, and religious communities, weakened by various social forces, are not able to support their members as they used to do. The result of all those changes is a more challenging life for midlife white people in the working-class, and they find significant disadvantages compared to the older generations.

Figure 2 shows the age-adjusted mortality rate of Americans in the 25 to 64 year-old age group that is attributable to drugs, suicide and alcohol. As the figure indicates, there is a strong uptrend for white people such that the mortality rate rose from 47.6 in 1999 to 108.0 in 2019—an increase of 126.9%. Also, while midlife mortality caused by despair is almost steady since 1999 to 2010 for Hispanics, there is a sudden drop for non-Hispanic Blacks (hereafter refered to as Blacks) that began in 2006 and continues to 2010. After 2010, there is a significant uptrend for midlife despair mortality of Blacks and Hispanics, which is contrary to Case and Deaton’s

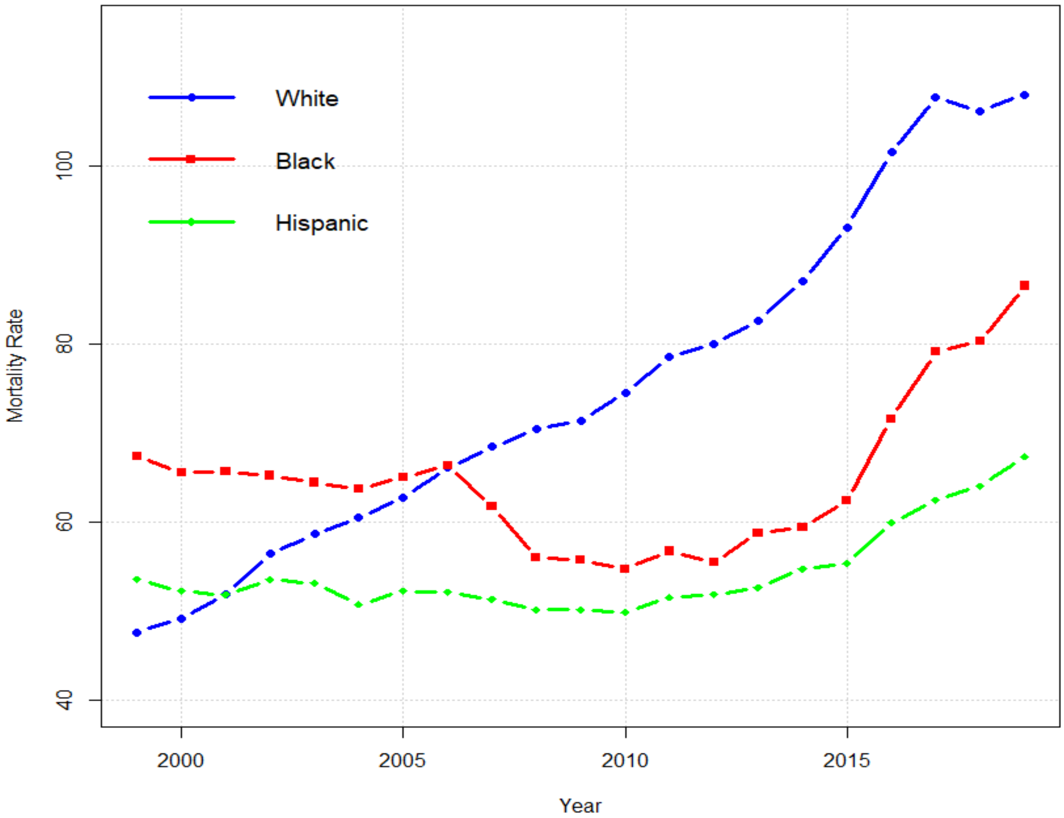


Figure 2. Age adjusted mortality rate among 25-64 year-old Americans attributable to drugs, suicide and alcohol by race/ethnicity, 1999-2019 (NCHS 2021)

argument that the rise in "deaths of despair" is happening only for non-Hispanic white Americans. As the figure 2 shows, mortality in 1999 was lower among whites than among Blacks and Hispanics. However, over time white mortality surpassed other racial/ethnic groups, confirming that the situation for midlife white people is becoming considerably more serious.

The growing deaths of despair is threatening a large vulnerable group of the American population and can be considered an urgent priority, necessitating further research on the topic. This dissertation defines its overarching goal as taking some steps toward a deeper understanding of the issue. I start with a literature review on the most important studies related to that topic. Then, I point to two major gaps of the existing literature, and according to those gaps, I design the main questions of this study as well as methods of analysis to answer the questions. I devote two chapters to review results that emerge from my analyses. Finally, in the last chapter, I discuss the most significant findings, future directions, limitations, and suggested policies.

Literature review

This literature review includes four subsets. First, I summarize studies that have addressed the deaths of despair (DoD) thesis in recent years. In the second section, I summarize studies focusing only on drug mortality, because the number of them is growing and they deserve more attention. The third section is related to studies that emphasize geographic disparities in DoD, which may reveal important differences across US states and other geopolitical entities. Finally, the fourth section is a summary of studies that attempt to provide an explanation for DoD generally or drug mortality in particular.

Deaths of Despair (DoD)

Case and Deaton’s (2015) work has attracted much attention from public media, as highlighted via a keyword search for “deaths of despair” on the Internet. This search returns a huge number of articles, interviews, and TV reports related to the matter. At the same time, many researchers in academia in different fields such as public health, epidemiology, sociology, demography, economics, and public policy have investigated deaths of despair. In what follows, I discuss several important studies on the issue.

Snyder (2016) attempts to refine Case and Deaton’s study in terms of urbanization. Using six levels of urbanization, from metropolitan areas to rural areas, he found that the 45 to 54 year-old group of non-Hispanic white Americans who lived in more urban areas experienced a 7.6 percent reduction in death rates from 1999 to

2013. As urbanicity declined in this age group, from somewhat less urban areas to more rural areas, mortality increased steadily from 6.3 to 76 percent in the same period.

In a short response to Case and Deaton (2015), Schmid (2016) contends that their explanations based on deaths of despair (including suicide, drug overdose, and alcohol abuse) only explain one-third of the observed mortality increase, necessitating another explanation for the remaining two-thirds. Gelamn and Auerbach (2016), in another response, argue that the pattern reported by Case and Deaton is at least partially due to age aggregation bias and the changing age composition of 45 to 54 year-old Americans. They show that the age distribution among 45 to 54 year-olds was skewed toward younger ages in 1999 but shifted toward older ages by 2013. They also add that the mortality increase for white women is more serious than that of men, and researchers need to take that point into consideration. Case and Deaton (2016) attempted to address some of the above-mentioned concerns by acknowledging that their initial study should be refined based on three factors: sex disparities, additional causes of death, and geographic areas.

Nevertheless, Case and Deaton (2017) refute the concern of age bias raised by Gelman and Auerbach (2016). To address that concern, they replicate their analysis by five-year age groups, instead of 10-year ones, and conclude the new results do not have any significant difference from their previous analysis. For example, the results for the 50 to 54 year-old group in the new study is only 0.09 of a year (or 33 days) off from the first study, and they argue that is negligible.

Shiels et al. (2017) investigate age groups between 25 to 64 years of age from 1999 to 2014, with more of a focus on sex, race and ethnicity differences. They confirm the increase in midlife mortality among white Americans, showing that the death rate increased among 30-year-old non-Hispanic white American women and men by 2.3 percent and 0.6 percent, respectively. However, in addition they observe an increase in death rates among American Indians and Alaska Natives. They also confirm that deaths of despair are mainly responsible for that increase. In contrast to non-Hispanic whites and American Indians and Alaska Natives, they find evidence of mortality declines among all age groups for Blacks (up to a 3.9% decrease), Hispanics (up to 3.2%), and Asians and Pacific Islanders (up to 2.6%). They assert that these declines are attributable to reductions in mortality related to HIV, cancer, cardiovascular diseases, and smoking cessation.

Woolf et al. (2018) examine the mortality of midlife Americans across racial and ethnic groups from 1999 to 2016. Like Shiels et al. (2017), their investigation concludes that mortality in midlife has not only increased for non-Hispanic whites, but also for Non-Hispanic American Indians and Alaskan natives. However, while all-cause midlife mortality for non-Hispanic Blacks, non-Hispanic Asians, Pacific Islanders, and Hispanics decreased until 2009-2011, it increased after those years. Drug poisoning is the main cause of midlife death increase in all racial and ethnic groups assessed in the study, and alcohol abuse, suicide, and organ diseases involving multiple body systems are in the next ranks. Also, they find that midlife mortality increase is different based on sex and levels of urbanization; deaths caused by drug overdoses are more common among women than men, and death rates from these causes are higher in small cities and non-metropolitan areas than in large urban centers.

In another analysis, Stein et al. (2017) inspect mortality among people between 25 to 64 years of age in two time periods, 1999 to 2001 and 2013 to 2015. The authors attempt to reveal nuances in the deaths of despair hypothesis by examining race, urbanization, and various specific causes of death. Like some other studies, their findings suggest a decrease in mortality among Blacks and Hispanics over the two periods, mainly due to improvements in motor vehicle collisions (MVC) and HIV in the 25 to 34 year-old group, and improvements in chronic diseases in the 45 to 64 year-old group. One important point is that among younger Blacks and Hispanics, the significant decrease in deaths due to these causes offsets the death increase caused by drug poisonings and suicides. They add that the most significant increase in mortality has happened among non-Hispanic whites in the 25 to 34 year-old group that lives in suburban areas, and especially among the 45 to 64 year-old group from rural areas. The growth of poverty in suburban areas and loss of manufacturing jobs in rural areas are suggested causes of those mortality increase by authors. They argue that their findings generally support the deaths of despair hypothesis.

Woolf and Schoomaker (2019) examine life expectancy and mortality data and find that, for the first time in the last six decades, U.S. life expectancy declined for three consecutive years after 2014. As an explanation for that decline, they refer to an increase in cause-specific mortality among 25 to 64 year-old people that started in the early 1990s, which eventually resulted in a rise in all-cause mortality that began in 2010. According to the authors, this increase is happening over all racial groups and is caused by drug, alcohol, suicide, and a variety of organ system diseases.

From Deaths of Despair to the Opioid Crisis

In the more recent literature, particularly after 2017, there are a number of studies focusing on deaths caused by drugs alone. For instance, Ruhm (2018a) argues that DoD is actually an opioid crisis. In this section, I summarize some of those studies.

Masters et al. (2017) study the mortality data of white people in the 45 to 54 age group from 1980 to 2013. Their findings point to two issues that are not consistent with the deaths of despair thesis and some earlier studies. Their first assertion is that while mortality among middle-aged white people caused by drug overdoses increased significantly from 1980 to 2013, mortality caused by suicide and chronic liver diseases was fairly stable over the same time period. Consequently, Masters et al. suggest that bundling the three causes of death commonly attributed to DoD (i.e., suicide, alcohol, and drugs) is not justifiable because drug poisoning has special importance. Another key argument in this study involves significant sex disparities in extrinsic causes of death (i.e., causes of death that are external to the body), as its findings suggest that there is not a common underlying factor that explains mortality increases for men and women. As a result, they believe that the singular theory for deaths of despair is not tenable because it assumes the U.S. mortality increase has a common cause rooted in hopelessness and distress regardless of sex.

In another study, Masters et al. (2018) examine mortality data among white Americans from 1980 to 2014 and add extrinsic causes of death as well as metabolic diseases (i.e. deaths from cardiovascular diseases, diabetes, obesity, and hypertension) to drug poisonings, alcohol abuse, and suicide. Again, they emphasize that deaths caused by drug poisonings have significantly increased since the 1990s, but the data show no such increase in mortality caused by alcohol or suicide. Furthermore, they argue that the drug mortality increase is not limited to middle-aged groups, but rather includes all ages from the 20s to 50s. They explain that increase by the rising availability of some opioids, as well as (1) misuse or over-prescription of some opioid-based painkillers by medical practitioners and (2) an increase in heroin use. Moreover, as in their previous study, they emphasize differences between men and women and argue that sex-specific explanations for rising mortality are necessary. For example, there has been a decline in deaths caused by metabolic disorders among middle-aged white American men, but this decline has stalled among women. They add that deaths caused by metabolic disorders are significantly higher among more recently born white people, confirming some other studies about an expanding obesogenic environment in the country (e.g. Olshansky 2005). In their conclusion, Masters et al. (2018) state that the expanding obesogenic environment along with the drug and opioid epidemic can provide a strong explanation for the increase in deaths among midlife white Americans.

In two separate studies, Ruhm (2018a, 2018b) focuses on drug death data from 1999 to 2015. Based on findings from these investigations, he asserts that deaths of despair are actually an opioid crisis happening rapidly throughout the US. He argues that counties in economic decline experience more drug deaths, but that relationship is not particularly strong; therefore, deaths of despair cannot be the main cause of drug overdoses. Ruhm (2018b) concludes that fatal drug overdoses are the main cause of the mortality increase among early-to-midlife whites, particularly in the 22 to 39 year-old age group; this association is stronger for men than women. Furthermore, illicit opioids have a stronger effect than prescription opioids on the increase in mortality.

Shiels et al. (2019) inspect trends in premature deaths (deaths between 25 and 64 years of age) due to (1) all causes and (2) drug poisoning between 2000 and 2015 among various racial/ethnic groups in the US population. According to the findings, the premature death rate (due to all causes) from 2000 to 2015 declined for Latino and black people and increased for white people, particularly whites living in less affluent and more rural counties. However, the death rate caused by drug poisoning rapidly increased among white, Latino, and Black men and women. This increase also happened in both rural and urban counties as well as more and less affluent counties. In terms of the absolute number of deaths (not the death rate) between 2012 and 2015, 75 percent of deaths caused by drug poisoning occurred in metropolitan counties while only one percent of deaths occurred in rural counties. Another significant point is that heroin is the most common cause of opioid deaths among white and Latino men, while prescription opioids are the most common cause among white and Latino women. Among both Black men and women, cocaine is the most common cause of drug poisoning death.

Kiang et al. (2019) focus on the geographic distribution of drug morality across the US and how that distribution has changed from 1999 to 2016. The study, which is based on individual-level survey data from the National Center for Health Statistics (NCHS), asserts that opioid mortality and especially synthetic opioid mortality has rapidly increased in most states but particularly in eastern states of the nation. Conversely, in most states, natural and semisynthetic opioid mortality has remained stable. The findings show, in 2016, overall opioid mortality caused the life expectancy of Americans to decrease by 0.36 years.

Spatial Disparities in DoD

In a follow-up note, Case and Deaton (2016) suggest their seminal paper should be refined by examining three factors, one of which is geography. Consistent with this suggestion, a number of studies in the literature assess geographic variations in mortality caused by drugs, alcohol, and suicide. For example, Squires and Blumenthal (2016) argue that states in the South, including Alabama, Arkansas, Kentucky, Mississippi, Oklahoma, Tennessee, and West Virginia, experience a more intense problem while the situation in the northeast is better. They conclude that social and economic factors such as low education, social isolation, disengagement from the economy, weakened communities, and the splintering of society based on social class and cultural lines are possible causes of this geographical variation in health disparities.

Dwyer-Lindgren et al. (2016) argue that the level of change in cause-specific mortality rates varies significantly across counties. For example, death rates from self-harm and interpersonal violence are highest in Alaska, on native-American reservations in North and South Dakota, and in southwestern states. Belluz and Frostenson (2017) argue that despite substantial advances in population health since 1980, some parts of the country could not take advantage of the advances. They assert that deaths caused by mental disorders and substance use are more concentrated around midwestern states like Pennsylvania, Ohio, Indiana, West Virginia, Kentucky, and Missouri, and deaths caused by self-harm and interpersonal violence are more prevalent in counties located in the southwestern part of the nation. In a second study, Dwyer-Lindgren et al. (2018) find that deaths caused by alcohol, drug, self-harm, and inter-personal violence also vary significantly across counties. Between 1980 and 2014, mortality rates from alcohol, self-harm, and interpersonal violence declined, on average, but that is not true for every county. Over the same time period, drug deaths increased for every U.S. county, but the level of increase was significantly different across counties.

Kiang et al. (2019) argue that opioid-related mortality is concentrated in Appalachian and midwestern states, but is now spreading rapidly among eastern states. They emphasize the role of synthetic opioids as the main culprit of the problem. Wilt et al. (2019) also find clusters of high drug mortality in eastern and midwestern states, which have significantly grown from 2000 to 2016. Woolf and Schoomaker (2019) show that states like New Hampshire, Maine, Vermont in New England, and West Virginia, Ohio, and Indiana, and Kentucky in Ohio Valley have experienced the highest midlife mortality rates caused by drug, alcohol, suicide, and a variety of organ system diseases since the beginning of the 1990s.

Explanations for DoD

In order to explain drug deaths or deaths of despair in general, some studies inspect the effects of economic, social, or environmental factors. Among these studies, some focus on a narrow subset of purported determinants. For example, Dean and Kimmel (2019) examine the effects of job loss and international trade on opioid mortality in 1999 and 2015; they find that trade-related job loss is significantly associated with opioid deaths. Hollingsworth et al. (2017) study how macroeconomic conditions (represented by unemployment) affect deaths or emergency department visits related to opioid overdose, and find significant associations between these measures at both county and state levels. Knapp et al. (2019) examine the effect of change in economic insecurity on deaths of despair between 2000 and 2015. They find that counties experiencing a higher level of economic insecurity have a higher level of mortality from DoD-related causes. Shiels et al. (2019) argue that counties with lower socioeconomic status suffered from a more rapid increase in drug mortality from 2000 to 2015. Zooroba and Salemi (2017) examine the effects of social capital on mortality caused by drug overdose from 1999 to 2014. After controlling for factors such as sociodemographic characteristics, the availability of substance abuse treatment, and opioid prescribing practices, they find that there is a significant negative association between social capital and drug mortality. These findings lead the authors to conclude that a high level of social capital protects the community against drug mortality.

Relative to these aforementioned studies, other investigations examine a wider range of variables. For instance, Monnat (2018) argues that there are significant geographic disparities in drug mortality such that in counties with economic hardships (including communities heavily dependent on mining) and family distress, the death rate is substantially higher than in counties with supporting religious organizations and a large number of new in-migrants. Interestingly, drug-related mortality rates are also higher in counties that are more reliant on the public sector job market. Another interesting finding from Monnat (2018) is that healthcare conditions do not have a significant effect on drug-related mortality. In a similar study, Monnat (2019a) inspects drug mortality in 2000 and 2015 and tries to explain increases over that period of time via socioeconomic variables and opioid supply. This study finds that economic and family distress, persistent population loss, and restrictions on opioid supply all have inverse associations with drug-related mortality among white people. Findings from this study also indicate significant variation between rural and urban areas; whereas illicit drug mortality increased most in large metropolitan and urban areas, prescription opioids played a more significant role in rural areas.

Monnat et al. (2019b) also examine associations between drug deaths and socioeconomic, demographic, and labor market characteristics of U.S. counties. They find that counties with socioeconomic disadvantages, more blue-collar and service-occupation labor, and higher opioid prescription rates tend to experience higher rates of overall drug mortality. Findings from this study also show that the economic and labor market conditions affect the type of opioid deaths. For example, more economically disadvantaged counties with larger working-class populations are associated with more deaths from combinations of synthetic and prescription opioids as well as prescription opioid deaths; conversely, urban, less economically disadvantaged counties with a high concentration of professional workers suffer from heroin and all other major opioid types of death.

Siddiqi et al. (2019) examine the trends and correlations between race, age, mortality, and a set of social and economic indicators from 2000 to 2016. Their investigation shows that increasing mortality among white Americans is not restricted to those with low education, but it is happening in higher education groups as well. In addition, neither short-term nor long-term economic variables can account for the increase. They emphasize the perception among whites that their social status is under threat as a factor explaining the rise in death rates.

Importance of the issue and gaps in the literature

After decades of advancement and improvement in health, the life expectancy of Americans began to stagnate in 2010. In addition to humanitarian concerns associated with this stagnation in longevity, which of course is the most important consideration, diminished health and reduced longevity may eventually have serious consequences for the financial health of the United States. For instance, if health conditions among midlife Americans deteriorate, one serious concern is that when they reach older ages, their health status will be worse than old age groups at the current time. Meara and Skinner (2015) contend that to the degree baby-boomers and subsequent generations are approaching retirement age with worse health conditions, expenditures for health programs such as Medicare, Medicaid, and Social Security Disability Insurance will increase substantially. Complicating the situation is health care spending in the U.S. that is already excessive. For instance, the U.S. spent $10,966 per capita on healthcare in 2019, which was 42% and 65% higher than Switzerland ($7,732) and Germany ($6,646), respectively, which are the second and third-leading countries with respect to per-capita health expenditures (Kamal et al. 2020).

Although the studies examined in my literature review address many facets of declining longevity in the U.S., there are still gaps and ambiguities in the literature. This dissertation focuses on two major issues that have not been addressed adequately by prior studies. First, as discussed, there is strong evidence that DoDs are not randomly distributed in the United States. For example, Dwyer-Lindgren et al. (2018) conclude that deaths caused by drug, alcohol abuse, self-harm, and interpersonal violence vary widely across counties, both in terms of mortality levels and trends. However, they do not discuss how the mortality trend in each region of the U.S. has changed over time. Similarly, Kiang et al. (2019) analyze opioid mortality trends in each state from 1999 to 2016, finding significant disparities in state-level trends. However, their study focuses only on opioid mortality, not other causes of DoD. The analyses in this dissertation will be the first to evaluate state-level mortality trends that includes all major causes of death (i.e. suicide, drugs, and alcohol) embedded in the DoD thesis.

Second, as Monnat (2018) argues, the contribution of social and economic factors to geographical variations of mortality is unknown, and more empirical research is necessary. Likewise, Shanahan et al. (2019) argue that although the term DoD has attracted much attention, there is not enough empirical evidence demonstrating how unfavorable socioeconomic conditions influence the level of despair in individuals. Therefore, another goal of this dissertation is to search for an explanation that is rooted in a thorough examination of the economic and social determinants of mortality increases related to DoD.

There are many different factors that affect human mortality. For example, (Rogers et al. 2019, p. 357) talk about four general distal causes including socioeconomic status, social relations, geographic variations, and human and environmental hazards that influence mortality through factors more proximate to death. Specific to deaths of despair, Shanahan et al. (2019) propose a theoretical roadmap suggesting how economic and social factors influence mortality attributable to alcohol, drugs, and suicide. In that framework, risk factors of despair include declining income, poor job prospects, disengagement from the labor force, loss of traditional family structure, and social isolation. Among these risk factors, the first three are related to the job market and economy, and the other two pertain to supportive communities and social capital. Similarly, Case and Deaton (2017) discuss the role of decline in the job market and economic prospects, especially for people with no college education, as well as the importance of supportive institutions like labor unions, family, and the church as main factors influencing deaths of despair.

Therefore, as far as data availability allows, I select measures for this study that reflect both economic and social variability across counties, as suggested by the above-mentioned studies.

In addition, a number of demographic variables are used as important covariates. Among those variables, two measures are related to the racal/ethnic composition of a county. One potential significant effect of racal/ethnic composition can be the social marginalization of white people. That is especially true for counties with a higher proportion of Hispanics in the population because there are studies that argue how the shared culture and social support in Hispanic neighborhoods and communities create ethnic enclaves (Pickett and Wilkinson 2008; Osypuk et al. 2009; Osypuk et al. 2010). Although such enclaves cause health benefits for Hispanics, they might bring about more isolation for other racial/ethnic groups. Another issue related to the racal/ethnic composition of a county may relate to the labor market. The educational attainment of Hispanics and Blacks on average is lower than that of whites. So it is reasonable to assume that in areas with larger Hispanic and Black populations, whites without college education experience more intense competition in the job market. The details of all selected variables are discussed in the Methods chapter.

There are other advantages in this study compared to prior investigations. While many studies use non-restricted versions of mortality data, and either exclude or impute the mortality rates of counties with fewer than 10 deaths, in this study I use restricted mortality data that includes all counties without suffering from data suppression. In addition, this study takes a crucial step beyond cross-sectional analysis by implementing fixed-effect panel and spatial models. There are numerous advantages of these models with respect to causal inference, which are discussed later in the Methods chapter. Also, this study implements a clear and thoughtful definition of DoD that is consistent with the original theory. Conflict between findings from prior studies and the ambiguity around the DoD hypothesis are traceable, in part, to inconsistent and unclear definitions. For example, some studies apply the DoD theory to all age groups of white Americans (e.g. Siddiqi et al. 2019), some do not distinguish between Hispanics and non-Hispanics whites (e.g. Masters et al. 2017), some assume that DoD are the equivalent of drug or opioid mortality (e.g. Ruhm 2018a; Monnat 2018), and so on. As discussed previously, the theory of deaths of despair, formulated by Case and Deaton (2015), refers to deaths among midlife non-Hispanic white Americans caused by three factors—drugs, alcohol, and suicide. So studies that do not follow that definition have deviated from the theory and they are testing something out of the scope and not explained by that theory. That's why in this dissertation, I return to the original definition provided by the creators of the DoD theory as much as possible, thereby providing a thorough empirical test that is faithful to its original conception.

Nevertheless, the trend analysis in this study is applied separately for each cause of despair-related mortality (i.e. drug, alcohol, and suicide). Because the nature of trend analysis is descriptive, the advantage of applying separate analysis for each cause is that we can isolate how each of these causes affects each state differently. However, for the explanative part of the study, I use the aggregate mortality caused by those three causes because the goal is to find a general explanation based on measures extracted from the theory of DoD. As that theory argue, those three causes are influenced by the same social and economic determinants and are the various manifestations of the same fundamental problems in American society, so the separation of the causes of deaths reduces the analysis to explain three different phenomena and misses the rationale of that theory.

CHAPTER II

METHODS

Questions

Based on the literature reviewed and arguments outlined in the introduction, I defined two main questions for this study: First, how do trends in mortality related to deaths of despair vary across the 50 states? Second, which predictor variables are most useful in explaining deaths of despair? For the first question, the units of analysis are states (e.g., Utah); to address this question, I use trend analysis. The units of analysis for the second question are counties (e.g., Cache County, Utah); to address this question I estimate different types of regression models, which I describe below.

Data

The data of this dissertation is from four sources including National Vital Statistics System, American Community Survey, Northeast Regional Center for Rural Development at Penn State University, and Bureau of Labor Statistics.

The main measure of trend analysis is the mortality rate of non-Hispanic whites aged 25 to 64 that is caused by drugs, alcohol, or suicide from 1999 to 2019, and the analysis includes all 50 states. That mortality rate is based on multiple cause of death data, and is age-adjusted by the direct method according to the 2000 Census population and are reported per 100,000 persons. Appendix A includes the ICD-10 codes for specific causes of death. The source of mortality data is restricted-use files of the National Vital Statistics System (NCHS 2019).

The panel data used in this study contains three points of observation: 2009, 2014, and 2019. The 2009 data set includes data collected by the ACS from 2005 to

2009, and the mortality rate covering the same period. However, owing to the lack of data for median income and Gini index in 2005 to 2009, I used data from 2006 to 2010 for those measures.

The 2014 data set includes data collected from 2010 to 2014 by the ACS, and the mortality rate covering the same period. The 2019 data set includes data collected from 2015 to 2019 by the ACS, and the mortality rate from 2015 to 2018, calculated from the most recent mortality data at the time of this study. Because the social capital index is only available for 2005, 2009, and 2014, I used those three years for the 2009, 2014, and 2019 data sets, respectively. This issue can have a potential benefit because the data of social capital belongs to almost the beginning of each data set (i.e. 2005, 2009, and 2014), so the influence of social capital on mortality has a built-in lag time. Also, I included the unemployment data for 2009, 2014, and 2019 in the corresponding panel data sets.

Due to the lack of data, two states (Alaska and Hawaii) as well as Broomfield County, Colorado were excluded from the panel data. Also, I dropped Bedford (independent) city, Virginia because it was merged to Bedford County in 2013. There is a total of 3,107 counties in the analysis.

Measures of panel data

Dependent variable

The dependent variable in this study is the mortality rate of non-Hispanic whites aged 25 to 64 that is attributable to drugs, alcohol, or suicide, based on multiple cause of death data. All mortality rates are age-adjusted by the direct method based on the 2000 Census population and are reported per 100,000 persons. The ICD-10 codes for specific causes of death in this study are included in appendix A. The source of mortality data is restricted-use files of the National Vital Statistics System (NCHS 2019). A significant advantage of restricted-use data over public-use data is that while the public-use data include only counties with deaths counts higher than 10, the restricted-use version contains all counties, regardless of death counts.

Independent variables

As discussed in the previous chapter, the independent variables in this investigation include a set of economic and social measures that reflect important concepts from the deaths of despair literature. Also, four demographic variables are selected as control variables. The demographic measures include

- Black Population %: The population of non-Hispanic Blacks in a county divided by the total population of the county multiplied by 100.
- Hispanic Population %: The population of Hispanics in a county divided by the total population of the county multiplied by 100.
- Median Age: Median age of people living in the county.
- Population Change: Population of the county in 2000 minus the population of the county at the end of data observation period (2009, 2014, or 2019) and then divided by 1000.

The source of all four demographic measures is the American Community Survey (5-year estimates) (U.S. Census Bureau 2014 and 2020). The economic and social measures include

- Social Capital Index: The index of social capital for each county. This index is constructed using principal component analysis from factors such as the number of religious, business, recreational and entertainment, political, professional, non-profit, etc. organizations, associations, and activities in a county divided by population size

(Penn State University's Department of Agricultural Economics Sociology and Education 2021).

- Married %: The population of married people divided by the total population over 15 years old, multiplied by 100.
- Population Density (log): This measure is the natural logarithm of the population of a county divided by the area of the county in square miles.
- Median Income: The median income of all households in a county.
- Unemployment %: The number of unemployed people divided by the sum of unemployed and employed people in a county multiplied by 100 (Bureau of Labor Statistics 2021).
- Gini Index: The measure of income inequality between 0 (perfect equality) to 1 (maximum inequality) for a county. According to the Census Bureau (2016) the index is calculated from the difference between the observed cumulative income distribution and a perfectly equal income distribution.
- People under the Poverty Line %: The population of people living under the poverty line divided by the total population over 15 years old in a county, multiplied by 100.
- People with at least Some College Education %: The number of people with some years of college or a college degree (associate to doctorate level) divided by the total population over 25 years old in a county multiplied by 100.

The source of data for all economic and social measures, except for the social capital index and unemployment rate, is the American Community Survey (5-year estimates) (U.S. Census Bureau 2014 and 2020). The social capital index is estimated by the Northeast Regional Center for Rural Development at Penn State University

(Rupasingha et al. 2006, with updates). Unemployment data is from Local Area Unemployment Statistics (Bureau of Labor Statistics 2020).

Analysis

Joinpoint Models

I used joinpoint regression to address the first main question of the study. Joinpoint regression, also named segmented regression or piecewise regression (Kim et al., 2000; Goovaerts and Xiao 2011; Hegerl et al., 2013), estimates the years when a significant change in DoD-related mortality trends occur for each individual state. The model starts with a single line estimation with no joinpoint and then tests to see whether the data warrant one or more joinpoints that reflect significant changes in the mortality trend. A series of Monte Carlo permutation tests are applied repeatedly between the model with fewer joinpoints and a more complicated one to determine the optimum number of joinpoints (Kim et al. 2000). I set the minimum joinpoint to zero and maximum to three which is the recommended number in the software documents for 21 years of data (National Cancer Institute 2020). Also, I set the minimum number of observations from a joinpoint to the end of the observation period as five. The slope of lines estimated by each joinpoint regression is the annual percentage change (APC) over the time interval of the study (1999 to 2019).

Fixed-effect panel model

To address the second major study question, I use fixed-effect panel models. The most important feature of such models is that they account for the unobserved time-constant unit-level heterogeneity (which in this study is unobserved county-level heterogeneity). From a sociological and public health standpoint, there are numerous variables in a county that can be assumed time- invariant and, at the same time, quantifying and measurement of such variables is difficult, if not impossible. Maybe the most important of those factors is social structure. Political economy and structural inequalities influence health disparities through social status, neighborhood segregation, racism, gender bias, etc (Stonington et al. 2018). Moreover, as the theory of health lifestyle discusses, the interplay of social structure and individuals shape behaviors such as smoking, drug abuse, alcohol drinking, exercise, sleep, diet, violence, use of healthcare, and so on (Hinote 2015; Hruschka 2009). Also, state membership of a county and all considerations related to that membership such as quality of healthcare, state tax and benefits, long-term economic and social programs, etc. are other examples of time-constant heterogeneities. Therefore, one of the significant advantages of applying fixed-effect models in this study, compared to previous cross-sectional analyses (e.g. Monnat 2018), is to eliminate, or at least reduce the bias of such time-invariant omitted determinants of health.

Unlike random effect models, unobserved time-constant heterogeneity can be correlated with the regressors (Wooldridge 2010; Nerlove 2005). Fixed-effect panel models are defined as:

$$y_{it} = X_{it}\,\beta + \alpha_i + u_{it} \quad (1)$$

Where y_{it} is a vector of the dependent variable for county i at time t; X_{it} is a vector of time-variant regressors; α_i is a vector of unobserved time-invariant county-level heterogeneity indicators; β are a vector of unknown parameters; and u_{it} are vectors of error terms. The interpretation of β is that one unit increase/ decrease in a predictor variable (e.g., X_1) of a county across time is associated with a β unit increase/decrease of the dependent variable in that county.

The fixed-effect model cancels α_i (unobserved time-invariant county effects) by demeaning both sides of equation (1) using within-group transformations:

$$(y_{it} - \bar{y}_i) = (X_{it} - \bar{X}_i)\,\beta + (\alpha_i - \bar{\alpha}_i) + (u_{it} - \bar{u}_i) \quad (2)$$

In fixed models, α_i is assumed to be constant; therefore $\alpha_i - \bar{\alpha}_i = 0$. Also, by assuming $y_{it} - \bar{y}_i = \ddot{y}_{it}$; $X_{it} - \bar{X}_i = \ddot{X}_{it}$; and $u_{it} - \bar{u}_i = \ddot{u}_{it}$, the equation (2) can be rewritten as:

$$\ddot{y}_{it} = \ddot{X}_{it}\,\beta + \ddot{u}_{it} \quad (3)$$

The model estimates β in equation (3) based on OLS regression of $\ddot{y}$ on $\ddot{X}$. This approach is equivalent to including a dummy variable for each unit of analysis (i.e. county) as a regressor such that equation 1 can be rewritten as:

$$y_{it} = X_{it}\,\beta + D1_i\,\alpha_1 + D2_i\,\alpha_2 + \cdots + Dn_i\,\alpha_n + u_{it} \quad (4)$$

Where $D1_i, D2_i, \ldots, Dn_i$ are dummy variables, with each dummy variable absorbing the particular effect of each county.

There are studies that discuss the pitfalls and limitations of fixed-effect panel models (e.g. Hill et al. 2020; Collischon and Eberl 2020; and Vaisey and Miles 2017; Elhorst 2012). I refer to three of those limitations which are more applicable to this analysis. First, the estimation of fixed-effect models is based on changes within counties over time, so one limitation of this model is that any measure that does not change over time cannot be estimated. Reverse causality is another potential problem of such models. Although the change in both dependent and independent variables may be significantly associated with each other, we cannot make sure of the direction of causality unless there is clear empirical evidence for that. The third potential limitation of fixed-effect panel models is related to time-varying unobserved heterogeneity. Although such models account for time-constant unobserved measures, they are still sensitive to the bias caused by omitting time-variant variables. Also, because the estimation is based on canceling the effect of omitted time-constant variables, there is no estimated coefficient for the effect of such variables, and it is unclear which biases are eliminated. Despite those limitations, several scholars welcome the growing use of fixed-effect panel models in sociology. For example, Collischon and Eberl (2020) argue that we can find similar limitations in other regression models, and they encourage applying fixed-effect panel models for specific kinds of research questions that involve change over time. I will come back to the potential influence of those limitations on the findings of this study in the discussion chapter.

Another issue to be considered in the analysis is the existence of cross-sectional dependency in the model because such dependency violates the assumption of independent observations and the estimations and inferences would not be reliable. In this study, because counties, as the unit of analysis, have a spatial nature, spatial dependence or spatial autocorrelation is the most significant type of such a dependency, justifying the use of spatial fixed-effect models.

Spatial fixed-effect panel model

According to the first law of geography, "everything is related to everything else, but near things are more related than distant things" (Tobler 1970:236). If we apply that law in this study, then counties closer to each other will have stronger mutual effects. Consequently, the measures derived for each county are under greatest influence from the characteristics of adjacent counties.

There are three potential sources of spatial dependency or spatial autocorrelation (Manski 1993; Fingleton 1999; Elhorst 2014). First, endogenous interaction effects originate from associations between the dependent variable of a unit (i.e. counties in this study) with the dependent variable of neighboring units. The model to address endogenous interaction is the spatial lag model or the spatial autoregressive model (SAR). Second, exogenous interaction effects are caused by associations between the independent variables of a unit with those of adjacent units; the spatial lag of X model (SLX) controls for that dependency by adding a spatial lag of independent variables to the model. The third type of spatial dependency originates from associations between omitted variables of units and appears as an autocorrelation in error terms. The spatial error model (SEM) is designed to address that type of dependency. When more than one type of spatial dependency exists, a combination of the aforementioned models—such as the spatial Durbin model (for type 1 and 2) or the spatial autoregressive combined model (for type 1 and 3)—is used (Elhorst 2010).

Global Moran's I is the most common test for spatial autocorrelations. Table 1 presents the result of that test for all measures used in this study, across the three data sets in the panel. The results suggest that there are significant autocorrelations for all measures including dependent and independent variables. Lagrange multiplier (LM) tests and the robust version of them are other tests applied to the residuals of non-spatial models to detect the presence of spatial lag and spatial error dependence (Burridge 1980; Anselin et al. 1996; Elhorst 2010). Table 2 shows the results of those tests applied to the residuals of a non-spatial fixed-effect panel model. The results suggest the presence of both lag and error spatial dependence (type 1 and 3) although the presence of lag dependence seems stronger.

Table 1. Global Moran's I test statistics on all measures

Measure	2009	2014	2019
Adj. Mortality Rate	0.087 ***	0.070 ***	0.082 ***
Black %	0.234 ***	0.233 ***	0.231 ***
Hispanic %	0.334 ***	0.336 ***	0.343 ***
Population Decline	0.041 **	0.050 ***	0.050 **
Median Age	0.086 ***	0.069 ***	0.056 ***
Social Capital Index	0.282 ***	0.224 ***	0.220 ***
Married %	0.112 ***	0.126 ***	0.110 ***
Population density (log)	0.152 ***	0.150 ***	0.148 ***
Median Income	0.136 ***	0.126 ***	0.125 ***
Unemployment %	0.126 ***	0.212 ***	0.146 ***
Gini Index	0.114 ***	0.114 ***	0.110 ***
Under Poverty Line %	0.186 ***	0.171 ***	0.155 ***
College Education %	0.169 ***	0.165 ***	0.164 ***

*= p<.05; **= p<.01;***= p<.001

Tables 2. Lagrange Multiplier tests for spatial dependence in panel models

Test	Test Statistic
Test for spatial lag dependence	245.29 ***
Test for spatial error dependence	50.88 ***
Robust test for spatial lag dependence sub spatial error	534.57 ***
Robust test for spatial error dependence sub spatial lag	340.16 ***

***= p<.001

The results of Global Moran's I and LM tests suggest that we should be concerned about all three types of endogenous, exogenous, and error interaction effects in the panel data. The most general model that addresses all three types of spatial dependency is called the Manski, SAC Durbin, or SARAR Durbin model and is defined based on this equation (Bivand 2011, LeSage and Pace 2009):

$$y_{it} = \rho W y_{it} + X_{it}\beta + WX_{it}\theta + u_{it} \quad (4)$$

$$u_{it} = \lambda W u_{it} + \varepsilon_{it} \quad (5)$$

In equations (4), (5), and (6), y_{it} is a vector of the dependent variable for county i at time t; X_{it} is a vector of regressors; W is the spatial weight matrix; ρ is a spatial autoregressive coefficient; θ and β are vectors of fixed and unknown parameters; λ is a spatial error coefficient; u_{it} and ε_{it} are vectors of error terms; Wy_{it} represents endogenous interaction effects among the dependent variables; WX_{it} represents exogenous interaction effects among the independent variables; and Wu_{it} represents interaction effects among the error terms.

Gibbons & Overman (2012) argue against the conventional routines of model selection merely based on statistics tests (e.g. Lagrange Multiplier tests, as discussed previously), indicating it is too mechanical to grasp the reality of spatial dependence. Vega & Elhorst (2015) address that issue by suggesting the SLX model as a point of departure because SLX is the simplest model among spatial models and produces flexible spillovers. In addition, the interpretation of direct and indirect (spillover) effects for that model is straightforward. That's why, in this study, I apply a SLX model as a spatial panel model. By assuming $\rho = \lambda = 0,$ the equations 4 and 5 are reduced to:

$$y_{it} = X_{it}\beta + WX_{it}\theta + \varepsilon_{it} \quad (6)$$

This is the equation for the SLX model. In equation (6), βs can be interpreted as direct effects while θs can be interpreted as indirect spatial effects (Vega & Elhorst 2015). The interpretation of β is the same as mentioned for the non-spatial fixed-effect panel model, and the interpretation of θ is one unit increase/decrease in a predictor variable (e.g., X_1) of a county over time is associated with a θ unit increase/decrease in the dependent variable in neighboring counties.

Spatial Weight Matrix (W)

A spatial weight matrix defines the spatial structure and connectedness of units (i.e. counties), and incorporates that structure into the econometric model (Anselin 1988). A weight matrix W is a square symmetric matrix and the element w_{ij} is equal to the spatial effect of unit j on unit i while all diagonal elements are zero. I define the weight matrix based on queen contiguity, which is the most common type. The matrix is defined as a binary matrix, meaning if county i and j are adjacent the value of the element w_{ij} is equal to one and otherwise that is equal to zero. However, the final matrix is row standardized such that each element w_{ij} is divided by the row-sum and takes a value between zero and one. The assumption is that the weight matrix is constant over the time period of the study.

Software

I used the software provided by the Surveillance Research Cancer Control and Population Sciences, NCI, ver. 4.9.0.0, to apply joinpoint models. I used R 4.03 and RStudio 1.3 for programming, data cleaning, and fitting the regression models. Also, I used ArcGIS 10.8 to produce maps.

CHAPTER III

FINDINGS OF TREND ANALYSIS

In the first section of the results, I present research findings on disparities in DoD-related mortality trends across states; this addresses the first main research question of this study. For each state, I include a separate trend analysis for each of the three causes of DoD (i.e. drug, alcohol, and suicide). The presentation of results begins with an examination of the overall trend in the US since 1999, and then continues with more detail for each state. Also, appendix B provides trends for each despair-related cause of mortality for all 50 states.

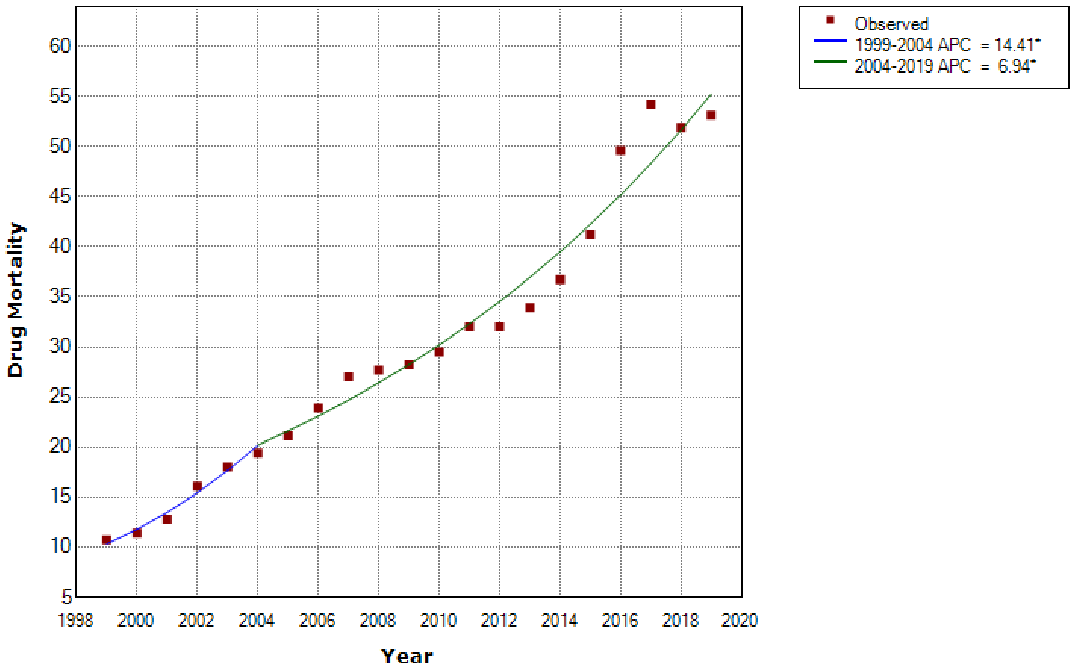
Drug mortality

Figure 3 shows the joinpoint trend of drug mortality for non-Hispanic white Americans in the 25 to 64 year-old age group. According to the graph, there is an overall uptrend in drug mortality after 1999. The most recent significant section of APC (annual percent change) is 6.9 meaning drug deaths for the U.S. population have increased by an average rate of 6.9 percent per year since 2013.

Table 3 presents drug-related mortality trends for each state. The first column is the most recent annual percentage change (APC) of drug mortality for each state, estimated by joinpoint regression. The second column is the average annual percentage change (AAPC) from 1999 to 2019. The third column is the age-adjusted drug mortality rate of each state in 2019 (per 100,000 persons). New Jersey, North Dakota, and Maryland with APC of 19.0, 18.0, and 17.6, respectively, have the highest drug mortality growth; Hawaii, Wyoming, and Utah with APC of -0.8, 1.2, and 1.3, respectively, have the lowest growth in recent years. However, in terms of level or rate of drug mortality in 2019, Delaware, West Virginia, and Maryland with 118.0, 117.2, and 87.8 deaths per 100,000, respectively, have the highest drug mortality rates while South Dakota, Nebraska, and Iowa with 20.1, 20.9, and 28.9 deaths per 100,000 have the lowest drug mortality rates.

Figure 4 and 5 show the spatial distribution of recent drug mortality growth and drug mortality level in 2019 by the state on the U.S. map. According to figure 4, states with the highest growth rates (with the exception of North Dakota) are located at the eastern side of the US; according to figure 5, states with the highest level of drug mortality (with exception of Nevada, Arizona, and New Mexico) are located in the Interwestern region of the US.

Figure 3. Trend of drug mortality in 25-64-year-old age group of whites, 1999-2019



* Indicates that the Annual Percent Change (APC) is significantly different from zero at the alpha = 0.05 level.
Final Selected Model: 1 Joinpoint.

Table 3. Drug mortality in 25-64 year-old age group among whites for each state

State	Last APC (95% CI)	AAPC (95% CI)	Age-Adj. Mortality Rate, 2019
Alabama	3.3* (1.5 to 5.1)	9.3* (5.2 to 13.5)	43.3 (40 to 46.7)
Alaska	4.5* (3.3 to 5.8)	4.5* (3.3 to 5.8)	45.7 (37.2 to 54.1)
Arizona	5.6* (5.2 to 6.1)	5.6* (5.2 to 6.1)	56.6 (53.2 to 60.1)
Arkansas	3.3* (1.4 to 5.4)	8.9* (7.3 to 10.5)	38.6 (34.8 to 42.4)
California	2.7* (2.1 to 3.3)	4.0* (1.7 to 6.4)	47.1 (45.6 to 48.6)
Colorado	3.2* (2.2 to 4.2)	5.4* (4.5 to 6.3)	36.9 (34.3 to 39.5)
Connecticut	16.9* (12.6 to 21.3)	9.7* (7.8 to 11.6)	74.7 (69.4 to 80)
Delaware	16.0* (11.6 to 20.6)	11.3* (6 to 16.9)	118 (104.8 to 131.1)
Florida	15.2* (9.2 to 21.5)	10.8* (6.3 to 15.4)	80.3 (77.8 to 82.9)
Georgia	5.0* (4 to 6.1)	8.9* (7.4 to 10.5)	36.1 (33.8 to 38.3)
Hawaii	-0.8 (-3.4 to 1.9)	4.0* (1.6 to 6.5)	35.2 (27.1 to 45.1)
Idaho	6.2* (5.2 to 7.3)	8.2* (6 to 10.4)	31.1 (27 to 35.2)
Illinois	8.6* (8.1 to 9.2)	8.6* (8.1 to 9.2)	42.7 (40.6 to 44.8)
Indiana	9.1* (7.8 to 10.3)	12.9* (11.3 to 14.4)	60.9 (57.8 to 63.9)
Iowa	5.4* (3.5 to 7.3)	11.8* (10.3 to 13.3)	28.9 (26 to 31.9)
Kansas	3.9* (2.5 to 5.2)	9.2* (7.5 to 10.9)	34.6 (31 to 38.2)
Kentucky	8.2* (7 to 9.5)	12.1* (10 to 14.3)	77.3 (73.2 to 81.4)
Louisiana	10.4* (6.8 to 14.1)	10.6* (8.4 to 12.9)	73.1 (68.4 to 77.7)
Maine	16.4* (10 to 23.3)	13.6* (8.3 to 19.2)	60.5 (54.1 to 67)
Maryland	17.6* (12.2 to 23.3)	9.5* (7.4 to 11.6)	87.8 (82.9 to 92.6)
Massachusetts	9.0* (7.8 to 10.2)	9.0* (7.8 to 10.2)	71 (67.5 to 74.4)
Michigan	6.7* (5.2 to 8.2)	8.8* (7.2 to 10.4)	49 (46.7 to 51.4)
Minnesota	4.7* (3.4 to 6)	9.6* (8.6 to 10.6)	29.4 (27.1 to 31.7)
Mississippi	1.3* (0 to 2.6)	7.8* (6.5 to 9.2)	42.5 (38 to 47.1)
Missouri	5.4* (4.2 to 6.6)	10.1* (9 to 11.2)	50.2 (47.3 to 53.1)
Montana	3.1* (1 to 5.1)	7.4* (4.5 to 10.4)	30.5 (25.3 to 35.7)
Nebraska	9.7* (8.2 to 11.2)	9.7* (8.2 to 11.2)	20.9 (17.5 to 24.3)
Nevada	3.0* (2 to 4)	5.1* (3.6 to 6.5)	55.7 (50.5 to 60.9)
New Hampshire	13.8* (11.6 to 16)	13.8* (11.6 to 16)	65.1 (58.4 to 71.9)
New Jersey	19.0* (16 to 22)	9.4* (7.6 to 11.3)	75.9 (72.2 to 79.6)
New Mexico	2.3* (0.4 to 4.1)	4.9* (3.4 to 6.3)	57.3 (49.3 to 65.3)
New York	8.5* (6 to 11)	9.3* (3.1 to 15.8)	39.9 (38.1 to 41.6)
North Carolina	6.4* (5.1 to 7.7)	10.0* (8.1 to 11.9)	53.9 (51.4 to 56.5)
North Dakota	18.0* (13.5 to 22.6)	18.0* (13.5 to 22.6)	29 (23.2 to 35.9)
Ohio	13.1* (11.8 to 14.5)	13.1* (11.8 to 14.5)	82.1 (79.4 to 84.9)
Oklahoma	2.5* (0.2 to 4.8)	8.7* (6.6 to 10.8)	45.6 (41.9 to 49.3)
Oregon	3.0* (1.7 to 4.3)	4.7* (3.5 to 5.9)	40.8 (37.7 to 43.8)
Pennsylvania	10.2* (9.1 to 11.3)	10.2* (9.1 to 11.3)	68.7 (66.2 to 71.1)
Rhode Island	7.3* (5.6 to 8.9)	10.0* (7.6 to 12.4)	66.2 (57.6 to 74.7)
South Carolina	9.8* (6 to 13.7)	9.9* (7.2 to 12.6)	60.1 (56.2 to 64)
South Dakota	4.6* (0.2 to 9.3)	12.7* (9.1 to 16.5)	20.1 (15.5 to 25.6)
Tennessee	9.4* (7.7 to 11.1)	11.4* (10.3 to 12.4)	73.6 (70.2 to 77)
Texas	2.7* (2.2 to 3.2)	5.3* (4.6 to 6)	32.4 (30.9 to 33.8)
Utah	1.3 (-0.1 to 2.7)	4.9* (3.4 to 6.4)	38.6 (35.1 to 42.1)
Vermont	12.6* (10.3 to 14.9)	10.5* (7.7 to 13.2)	51.1 (42.3 to 59.8)
Virginia	11.6* (8.6 to 14.7)	9.2* (4.5 to 14)	41 (38.5 to 43.5)
Washington	5.6* (2 to 9.3)	5.0* (3.6 to 6.4)	41.1 (38.7 to 43.5)
West Virginia	13.2* (10.9 to 15.6)	13.2* (10.9 to 15.6)	117.2 (109.4 to 125)
Wisconsin	9.6* (7.3 to 11.9)	11.1* (7.4 to 14.9)	40.1 (37.5 to 42.8)
Wyoming	1.2 (-3.2 to 5.9)	9.6* (5.9 to 13.4)	33.1 (26.1 to 41.4)

*= p<.05

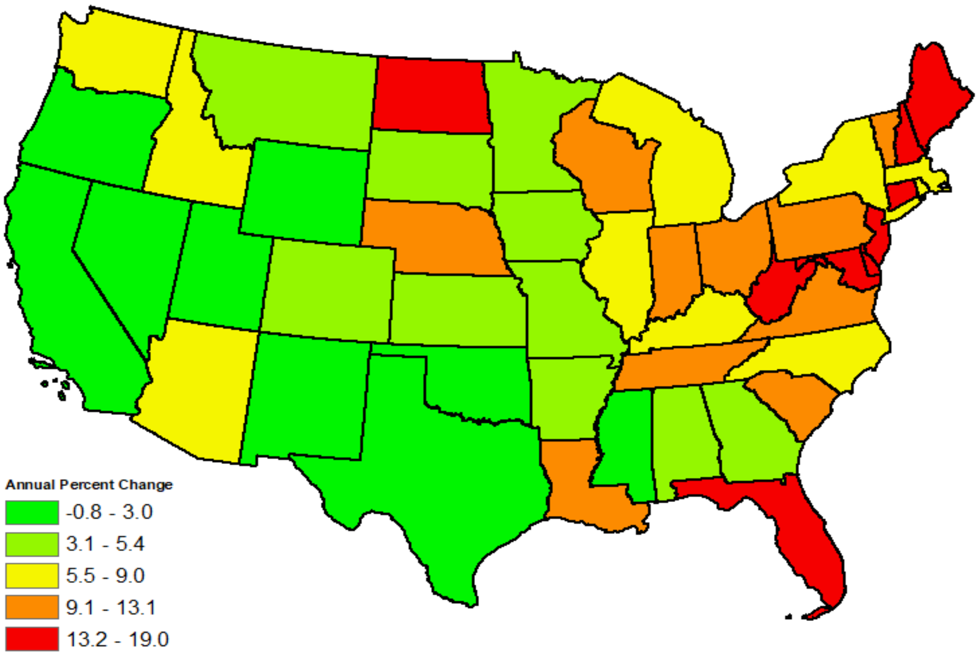


Figure 4. Drug mortality growth in the 25-64 year-old age group among whites

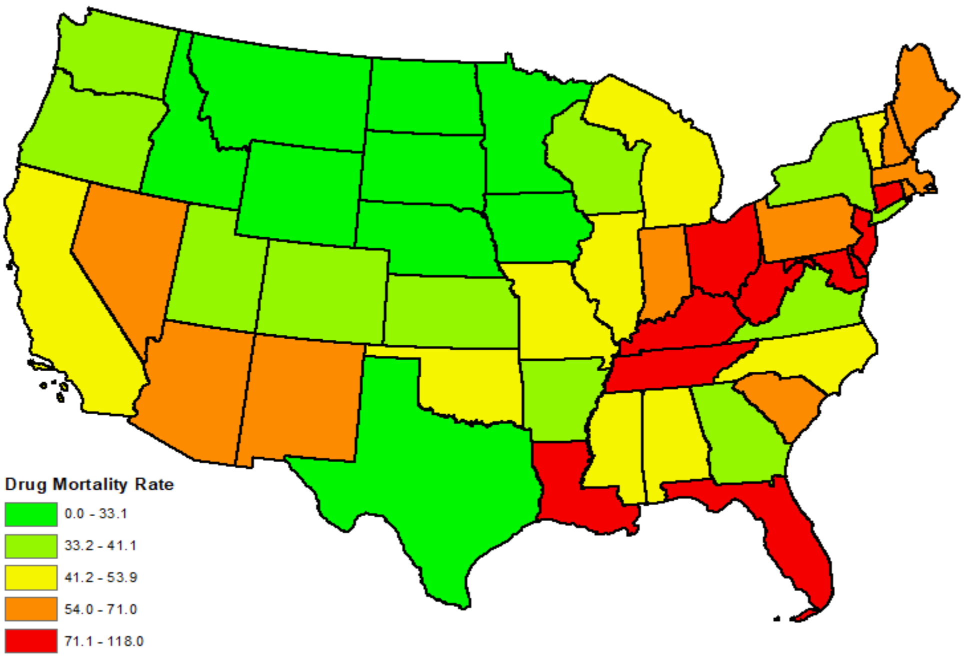


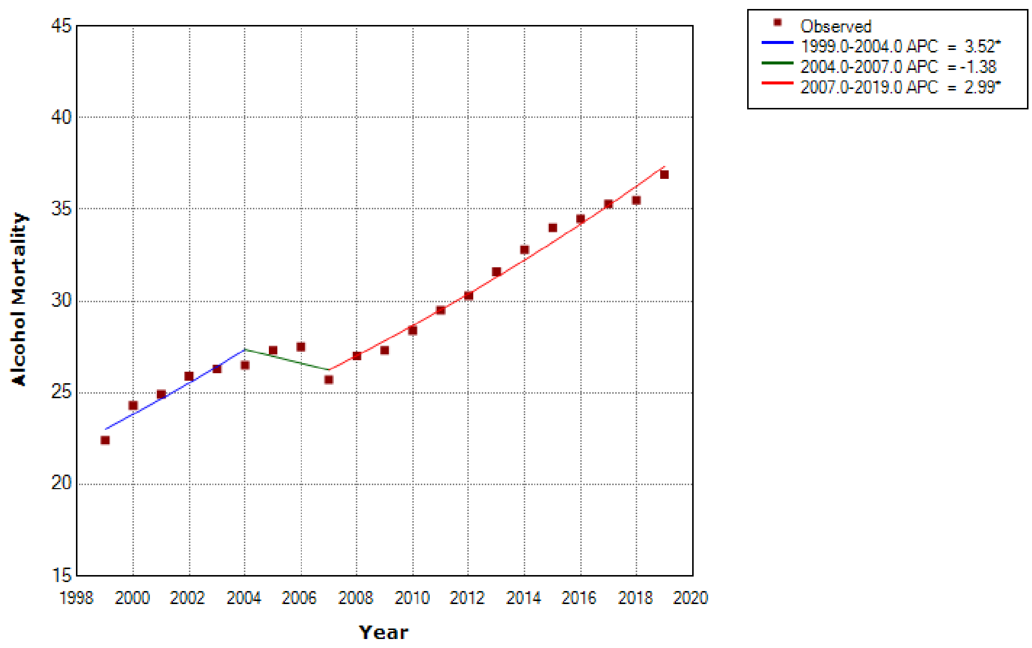
Figure 5. Drug mortality rate in the 25-64 year-old age group among whites, 2019

Alcohol mortality

Figure 6 presents the trend in alcohol mortality for the entire US population. According to the graph, the most recent significant section of APC (annual percent change) is 2.99, meaning that alcohol-related deaths in the US population have increased by an average rate of 2.99 percent per year since 2008.

Table 4 provides information about alcohol mortality for each state. The first column is the most recent significant annual percentage change (APC) of alcohol mortality for each state. The second column is the average annual percentage change (AAPC) from 1999 to 2019, and the third column is the adjusted alcohol mortality rate for each state in 2019 (per 100,000).

Figure 6. Trend of alcohol mortality in the 25-64 year-old group among whites, 1999-2019



* Indicates that the Annual Percent Change (APC) is significantly different from zero at the alpha = 0.05 level.
Final Selected Model: 2 Joinpoints.

Table 4. Alcohol mortality in the 25-64 year-old age group among whites for each state

State	Last APC (95% CI)	AAPC (95% CI)	Age-Adj. Mortality Rate, 2019
Alabama	2.6* (2.2 to 3.1)	2.6* (2.2 to 3.1)	36.5 (33.8 to 39.3)
Alaska	2.5* (1.3 to 3.7)	2.5* (1.3 to 3.7)	36.3 (29.1 to 43.5)
Arizona	0.5 (-2.1 to 3.3)	2.3 (-0.3 to 5)	41.8 (39 to 44.5)
Arkansas	3.3* (2.8 to 3.9)	3.3* (2.8 to 3.9)	38.9 (35.4 to 42.4)
California	0.4 (-0.1 to 0.8)	1.3* (0.7 to 2)	37.7 (36.4 to 39)
Colorado	2.2* (1.8 to 2.7)	2.2* (1.8 to 2.7)	49.7 (46.8 to 52.6)
Connecticut	6.3* (4 to 8.6)	1.7* (0.5 to 3)	31 (28 to 34)
Delaware	0.6 (-0.3 to 1.5)	0.6 (-0.3 to 1.5)	40.8 (33.9 to 47.7)
Florida	1.4 (-0.5 to 3.4)	2.2* (0.7 to 3.6)	47.9 (46.1 to 49.6)
Georgia	3.4* (2.7 to 4.1)	1.9* (0.7 to 3.1)	31.5 (29.5 to 33.4)
Hawaii	-0.8 (-3.2 to 1.7)	2.6* (1 to 4.2)	37.6 (29.3 to 47.6)
Idaho	4.0* (3.4 to 4.6)	4.0* (3.4 to 4.6)	40.4 (36 to 44.8)
Illinois	3.8* (2.5 to 5.2)	2.0* (1.2 to 2.7)	29.7 (28.1 to 31.3)
Indiana	3.5* (1 to 6)	3.5* (1.2 to 5.8)	39.3 (37.1 to 41.6)
Iowa	4.4* (3.9 to 5)	4.4* (3.9 to 5)	36.7 (33.6 to 39.8)
Kansas	3.2* (1.9 to 4.5)	2.9* (0.1 to 5.8)	34.7 (31.3 to 38)
Kentucky	5.9* (4.7 to 7.1)	3.8* (2.9 to 4.7)	48.4 (45.5 to 51.4)
Louisiana	-1.6 (-4.9 to 1.8)	1.1 (-1.2 to 3.5)	30.1 (27.4 to 32.8)
Maine	2.1* (1.5 to 2.7)	2.1* (1.5 to 2.7)	29 (25.1 to 32.9)
Maryland	6.2* (3.4 to 8.9)	1.8* (0.7 to 2.9)	33.3 (30.5 to 36)
Massachusetts	1.2* (0.6 to 1.8)	1.2* (0.6 to 1.8)	32.6 (30.5 to 34.7)
Michigan	1.7* (1.3 to 2)	1.7* (1.3 to 2)	33.5 (31.7 to 35.2)
Minnesota	4.4* (3.8 to 5)	2.3* (1 to 3.7)	35.6 (33.3 to 37.9)
Mississippi	1.8* (1.3 to 2.3)	1.8* (1.3 to 2.3)	41.1 (37 to 45.2)
Missouri	1.1* (0.4 to 1.9)	1.1* (0.4 to 1.9)	32 (29.9 to 34.2)
Montana	1.1* (0.2 to 1.9)	2.3* (1 to 3.5)	43.1 (37.3 to 48.8)
Nebraska	8.8* (5.1 to 12.7)	5.3* (3.8 to 6.7)	32.1 (28.2 to 36)
Nevada	0.8 (-1.1 to 2.8)	1.4 (-1.1 to 4)	57.9 (52.9 to 63)
New Hampshire	5.6* (3.5 to 7.7)	3.4* (2.3 to 4.6)	39.1 (34.3 to 43.8)
New Jersey	2.5* (1.2 to 3.9)	0.8 (0 to 1.7)	25.7 (23.9 to 27.6)
New Mexico	3.7* (2.9 to 4.4)	3.7* (2.9 to 4.4)	62.6 (54.7 to 70.6)
New York	1.8* (1.4 to 2.1)	1.8* (1.4 to 2.1)	21.8 (20.6 to 23)
North Carolina	0.8 (-1.3 to 3)	1.9 (-0.1 to 3.9)	38.2 (36.3 to 40.2)
North Dakota	4.6* (3.4 to 5.9)	4.6* (3.4 to 5.9)	40.7 (33.6 to 47.7)
Ohio	4.3* (3 to 5.5)	3.1* (1.5 to 4.9)	35 (33.4 to 36.6)
Oklahoma	3.7* (3.1 to 4.3)	3.7* (3.1 to 4.3)	49.7 (46.1 to 53.2)
Oregon	2.3* (1.7 to 2.9)	3.7* (2.9 to 4.5)	49.8 (46.6 to 53)
Pennsylvania	2.2* (1.2 to 3.3)	2.7* (0.5 to 4.9)	26.6 (25.2 to 27.9)
Rhode Island	2.7* (0.7 to 4.8)	3.2* (0.7 to 5.7)	54.7 (47.5 to 61.9)
South Carolina	3.3* (2.2 to 4.3)	2.0* (1.2 to 2.8)	42.1 (39.1 to 45)
South Dakota	4.3* (3.3 to 5.3)	4.3* (3.3 to 5.3)	39.1 (32.8 to 45.3)
Tennessee	4.7* (4.1 to 5.4)	3.4* (2.4 to 4.5)	48.4 (45.9 to 51)
Texas	1.6 (-0.2 to 3.3)	2.1* (1 to 3.3)	39.3 (37.9 to 40.8)
Utah	2.4* (1.8 to 3.1)	2.4* (1.8 to 3.1)	27.9 (24.9 to 30.8)
Vermont	3.0* (2.2 to 3.8)	3.0* (2.2 to 3.8)	35.9 (29.6 to 42.1)
Virginia	3.0* (2.6 to 3.5)	3.0* (2.6 to 3.5)	31.6 (29.6 to 33.7)
Washington	1.3* (0.3 to 2.4)	2.8* (2.1 to 3.5)	41 (38.8 to 43.3)
West Virginia	5.7* (4.1 to 7.3)	3.6* (2.6 to 4.6)	60.8 (55.6 to 66)
Wisconsin	3.7* (2.4 to 5)	2.3* (1.5 to 3.2)	36.6 (34.4 to 38.9)
Wyoming	4.1* (3.3 to 5)	4.1* (3.3 to 5)	71.7 (61.3 to 82.1)

*= p<.05

According to the table 4, Nebraska, Connecticut, and Maryland with APC of 8.8, 6.3, and 6.2, respectively, have the highest growth in alcohol-related mortality; Louisiana, Hawaii, and California with APC of -1.6, -0.8, and 0.4, respectively, have the lowest growth in recent years. However, in terms of the level of alcohol mortality in 2019, Wyoming, New Mexico, and West Virginia with 71.7, 62.6, and 60.8 deaths per 100,000, respectively, have the highest alcohol mortality rates while New York, New Jersey, and Pennsylvania with 21.8, 25.7, and 26.6 deaths per 100,000 have the lowest alcohol mortality rates.

Figure 7 and 8 show the spatial distribution of recent alcohol mortality growth and alcohol mortality level in 2019 for each state on the U.S. map. The maps suggest significant differences in the spatial distribution of mortality growth and mortality level. Moreover, the distribution of both growth and level of alcohol mortality is significantly different across states in comparison to the growth and level of drug mortality. States with the highest growth in alcohol-related mortality are mostly on the Western side of the US, which is the opposite pattern observed for drug mortality. As noted previously, growth in drug mortality is primarily concentrated in Eastern US states.

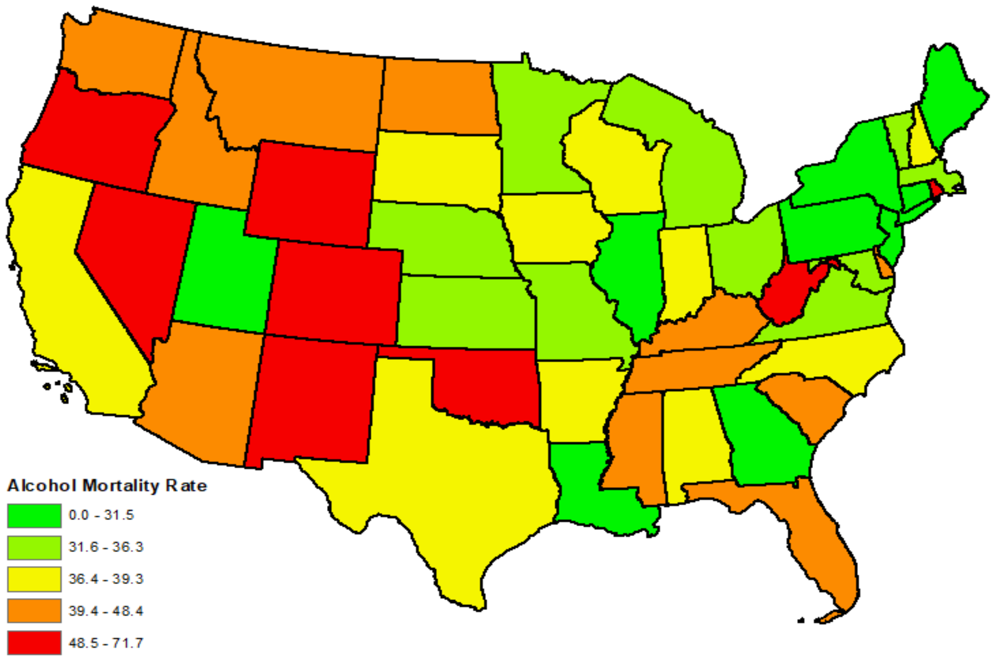


Figure 7. Alcohol mortality growth in the 25-64 year-old age group among whites

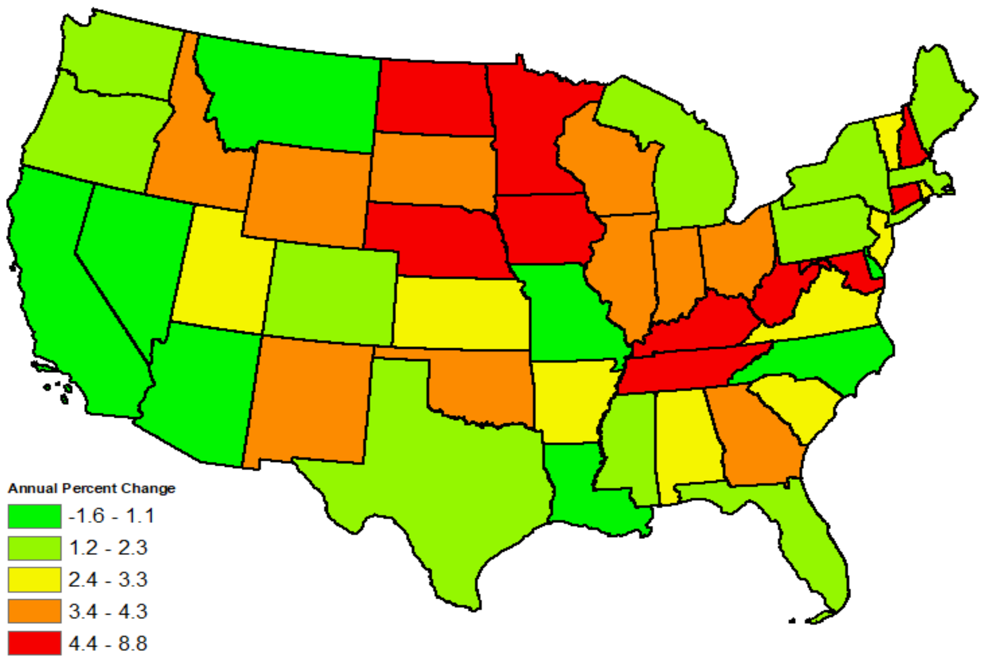


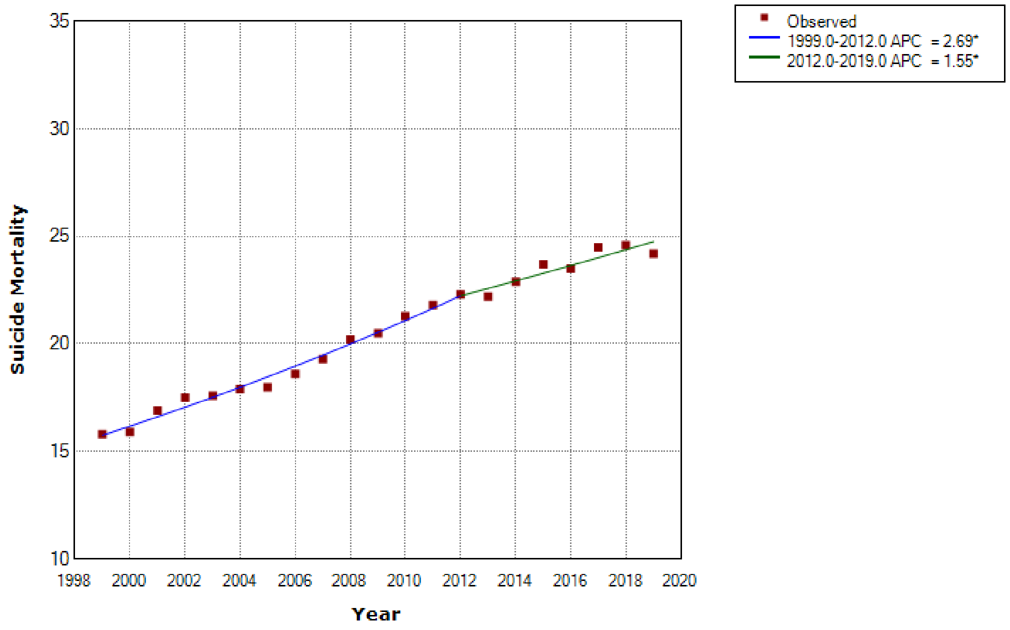
Figure 8. Alcohol mortality rate in the 25-64 year-old age group among whites, 2019

Suicide mortality

Figure 9 presents the trend in suicide mortality for the US population. According to the graph, the most recent significant change in APC (annual percent change) is 1.55 meaning suicide deaths for the US population have increased by a rate of 1.55 percent per year since 2010. Although the overall trend is still increasing, the current growth in suicide mortality is slower than growth between 1999 to 2012.

Table 5 provides information about suicide mortality levels and trends for each state. The first column is the most recent significant annual percentage change (APC) of suicide mortality for each state, estimated by joinpoint regression. The second column is the average annual percentage change (AAPC) from 1999 to 2019. The third column is the adjusted suicide mortality rate of each state in 2019 (per 100,000).

Figure 9. Trend of suicide mortality in 25-64 year-olds among whites, 1999-2019



* Indicates that the Annual Percent Change (APC) is significantly different from zero at the alpha = 0.05 level.
Final Selected Model: 1 Joinpoint.

Table 5. Suicide Mortality in the 25-64 year-old age group among whites for each State

State	Last APC (95% CI)	AAPC (95% CI)	Age-Adj. Mortality Rate, 2019
Alabama	2.1* (1 to 3.2)	2.0* (0.7 to 3.4)	29.3 (26.6 to 32.1)
Alaska	2.5* (1.5 to 3.5)	2.5* (1.5 to 3.5)	28.6 (22.4 to 36)
Arizona	-0.2 (-2.3 to 2)	1.8* (0.9 to 2.6)	31.5 (29 to 34.1)
Arkansas	2.8* (2.3 to 3.4)	2.8* (2.3 to 3.4)	30.1 (26.8 to 33.4)
California	0.2 (-1 to 1.4)	1.8* (1 to 2.6)	22.4 (21.3 to 23.4)
Colorado	2.3* (1.8 to 2.8)	2.3* (1.8 to 2.8)	32.5 (30 to 34.9)
Connecticut	2.7* (2.1 to 3.3)	2.7* (2.1 to 3.3)	19.8 (17.1 to 22.4)
Delaware	1.3* (0.4 to 2.3)	1.3* (0.4 to 2.3)	23 (17.7 to 29.5)
Florida	0.6 (-0.2 to 1.4)	1.6* (1.1 to 2.2)	29 (27.5 to 30.5)
Georgia	2.6* (2.2 to 3)	2.6* (2.2 to 3)	28.7 (26.7 to 30.7)
Hawaii	3.1* (1.5 to 4.7)	3.1* (1.5 to 4.7)	30.7 (23 to 40.3)
Idaho	2.9* (2 to 3.8)	2.9* (2 to 3.8)	26.6 (22.8 to 30.4)
Illinois	2.5* (2.1 to 2.8)	2.5* (2.1 to 2.8)	19.3 (18 to 20.7)
Indiana	2.3* (1.8 to 2.9)	2.3* (1.8 to 2.9)	21.7 (19.9 to 23.5)
Iowa	2.9* (2.5 to 3.4)	2.9* (2.5 to 3.4)	24.5 (21.8 to 27.2)
Kansas	2.8* (2.2 to 3.5)	2.8* (2.2 to 3.5)	27 (23.8 to 30.2)
Kentucky	2.1* (1.8 to 2.5)	2.1* (1.8 to 2.5)	25.7 (23.4 to 28)
Louisiana	2.5* (2 to 2.9)	2.5* (2 to 2.9)	27.8 (25 to 30.6)
Maine	2.8* (2 to 3.6)	2.8* (2 to 3.6)	27.9 (23.6 to 32.1)
Maryland	1.9* (1.5 to 2.2)	1.9* (1.5 to 2.2)	19.5 (17.3 to 21.8)
Massachusetts	1.3 (0 to 2.5)	2.5* (0.9 to 4.1)	15 (13.5 to 16.5)
Michigan	1.8* (1.4 to 2.2)	2.3* (1.8 to 2.8)	21.8 (20.3 to 23.4)
Minnesota	2.3* (1.7 to 2.9)	3.0* (2.4 to 3.5)	21.1 (19.2 to 23)
Mississippi	0.3 (-1.6 to 2.1)	2.0* (0.8 to 3.2)	27.6 (24 to 31.3)
Missouri	2.8* (2.5 to 3.2)	2.8* (2.5 to 3.2)	28 (25.8 to 30.1)
Montana	2.5* (1.8 to 3.2)	2.5* (1.8 to 3.2)	32.6 (27.3 to 38)
Nebraska	5.0* (2.7 to 7.3)	2.2* (0.7 to 3.7)	26.1 (22.4 to 29.8)
Nevada	1.2* (0.7 to 1.7)	1.2* (0.7 to 1.7)	37.4 (33.1 to 41.7)
New Hampshire	3.7* (2.8 to 4.5)	3.7* (2.8 to 4.5)	24.7 (20.7 to 28.7)
New Jersey	2.4* (1.8 to 3)	2.4* (1.8 to 3)	14.8 (13.3 to 16.4)
New Mexico	2.1* (1.4 to 2.9)	2.1* (1.4 to 2.9)	36.6 (30.3 to 42.9)
New York	0.3 (-1.4 to 1.9)	2.4* (1.1 to 3.7)	14.6 (13.5 to 15.6)
North Carolina	1.5* (1.2 to 1.9)	1.5* (1.2 to 1.9)	22.2 (20.6 to 23.8)
North Dakota	4.4* (3.5 to 5.3)	4.4* (3.5 to 5.3)	28.1 (22.4 to 34.8)
Ohio	2.7* (2.3 to 3.2)	2.7* (2.3 to 3.2)	22.8 (21.4 to 24.2)
Oklahoma	0 (-3.2 to 3.4)	1.6* (0.4 to 2.9)	30.8 (27.8 to 33.8)
Oregon	2.1* (1.5 to 2.6)	2.1* (1.5 to 2.6)	29.9 (27.3 to 32.6)
Pennsylvania	2.5* (2.1 to 2.8)	2.5* (2.1 to 2.8)	22.1 (20.7 to 23.4)
Rhode Island	3.2* (1.8 to 4.6)	3.2* (1.8 to 4.6)	20.6 (16.3 to 25.7)
South Carolina	2.6* (2.2 to 2.9)	2.6* (2.2 to 2.9)	27.9 (25.2 to 30.5)
South Dakota	2.7* (1.8 to 3.6)	2.7* (1.8 to 3.6)	24.9 (19.8 to 30.8)
Tennessee	1.9* (1.5 to 2.2)	1.9* (1.5 to 2.2)	26.8 (24.8 to 28.9)
Texas	2.3* (2.1 to 2.6)	2.3* (2.1 to 2.6)	27.8 (26.4 to 29.1)
Utah	2.9* (2.3 to 3.5)	2.9* (2.3 to 3.5)	32.7 (29.4 to 35.9)
Vermont	2.8* (2 to 3.7)	2.8* (2 to 3.7)	23.1 (17.8 to 29.6)
Virginia	2.0* (1.6 to 2.4)	2.0* (1.6 to 2.4)	21.4 (19.6 to 23.2)
Washington	1.8* (1.4 to 2.2)	1.8* (1.4 to 2.2)	24.2 (22.4 to 26.1)
West Virginia	2.7* (2 to 3.5)	2.7* (2 to 3.5)	26.9 (23.2 to 30.7)
Wisconsin	2.2* (1.7 to 2.7)	2.2* (1.7 to 2.7)	20.6 (18.7 to 22.4)
Wyoming	3.0* (2.1 to 3.9)	3.0* (2.1 to 3.9)	40.1 (32.3 to 49.2)

*= p<.05

According to table 5, Nebraska, North Dakota, and New Hampshire with APC of 5.0, 4.4, and 3.7, respectively, have the highest growth in suicide mortality. Conversely, Arizona, Oklahoma, and California, with APC of -0.2, 0.0, and 0.2, respectively, have the lowest growth in recent years. However, in terms of the level of suicide mortality in 2019, Wyoming, Nevada, and New Mexico with 40.1, 37.4, and 36.6 deaths per 100,000, respectively, have the highest suicide mortality rates. New York, New Jersey, and Massachusetts with 14.6, 14.8, and 15.0 deaths per 100,000, respectively, have the lowest suicide mortality rates.

Figure 10 and 11 show the spatial distribution of recent suicide mortality growth and suicide mortality rate or level in 2019 by state. Like drug and alcohol mortality, the maps suggest significant differences between mortality growth and mortality level. In addition, the distribution of both growth and level of suicide mortality is significantly different from those of alcohol, and especially, drug mortality.

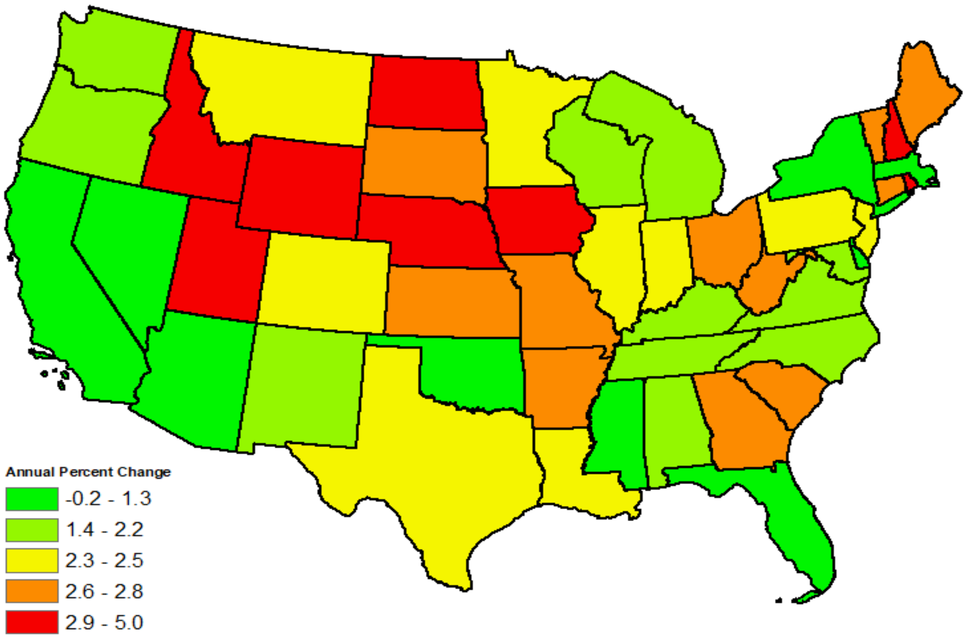


Figure 10. Suicide mortality growth in the 25-64 year-old age group among whites

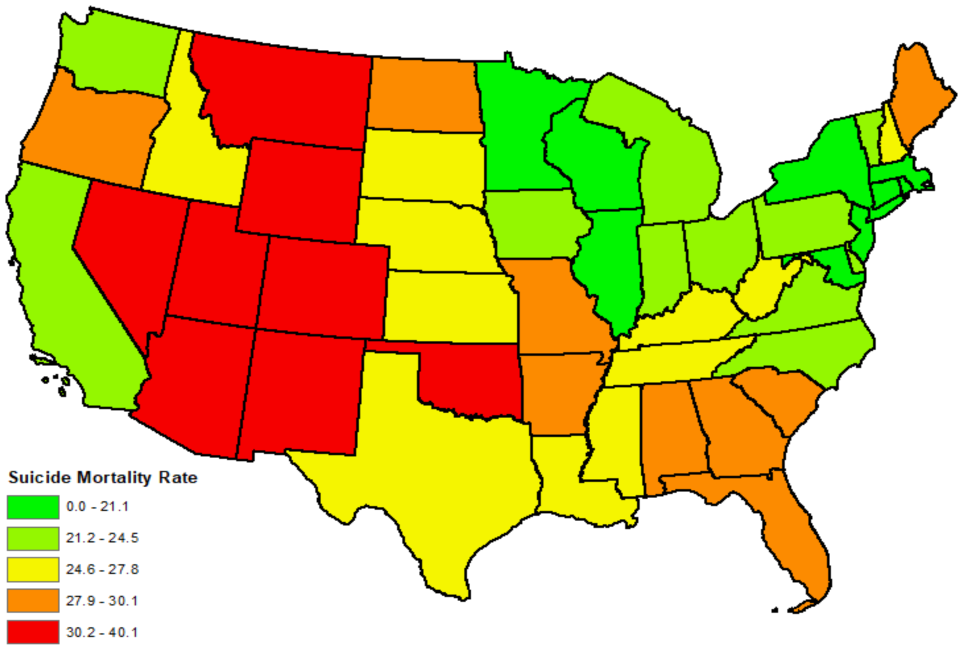


Figure 11. Suicide mortality rate in the 25-64 year-old age group among whites, 2019

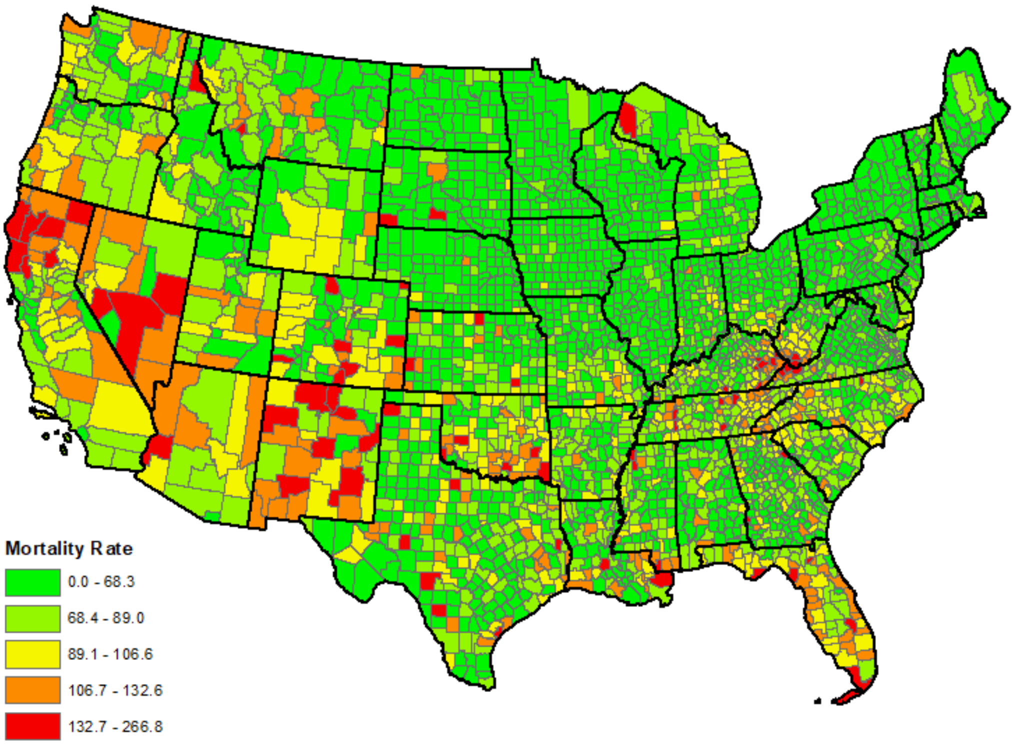
CHAPTER IV

FINDINGS OF AN EXPLANATION FOR DOD

In this section of the dissertation, I present results that address the second research question—namely which variables predict within-county changes in DoD-related causes of mortality. As discussed in the methods chapter, I applied a non-spatial fixed-effect panel model, as well as a SLX fixed-effect panel model to account for at least some parts of the spatial dependence. Before presenting the results of those models, I will discuss the results of some descriptive analyses.

Figure 12 to 14 present the spatial distribution of DoD in three sets of panel data (i.e. 2005-2009, 2010-2014, and 2015-2019).

Figure 12. DoD-attributable mortality rate (per 100,000 persons), 2005 to 2009



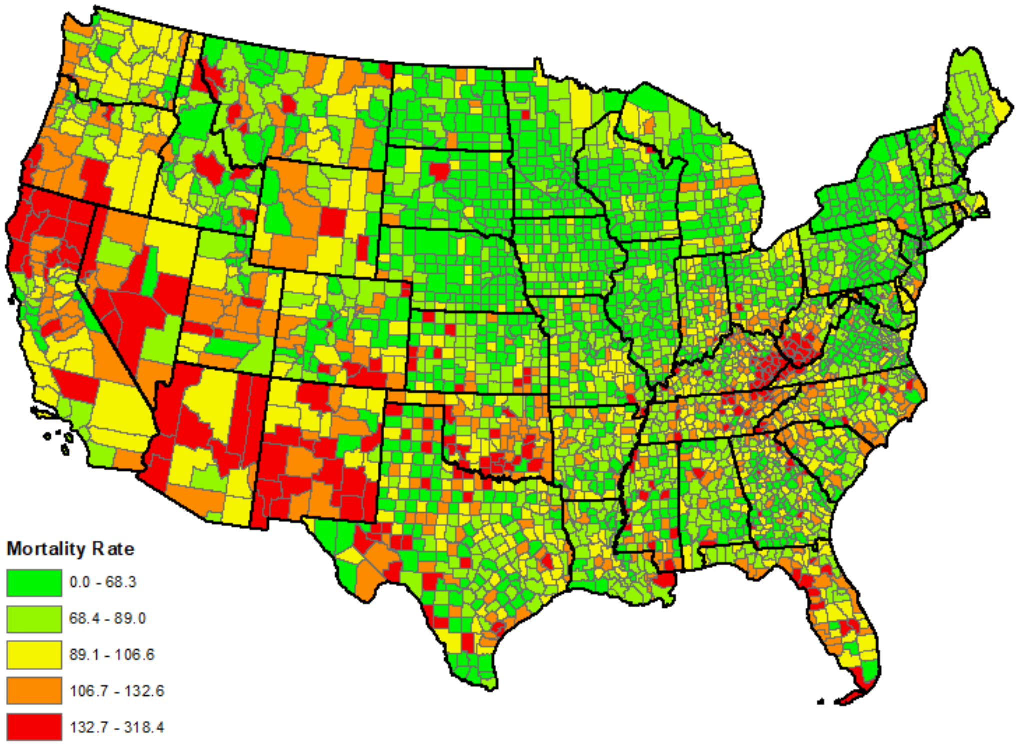


Figure 13. DoD-attributable mortality rate (per 100,000 persons), 2010 to 2014

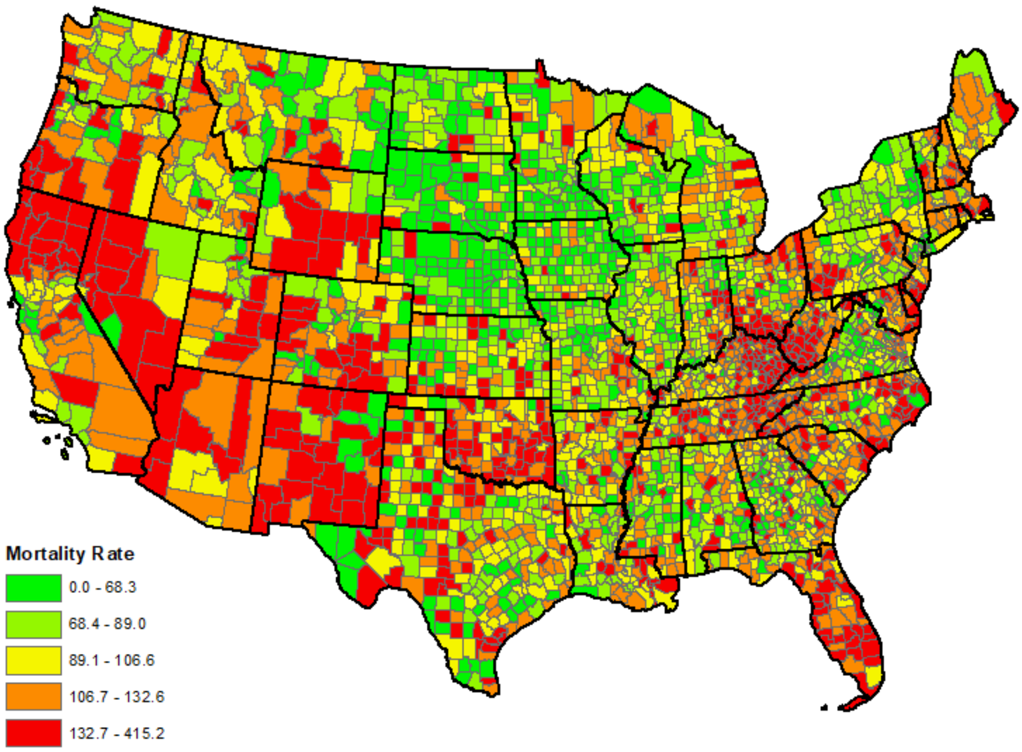


Figure 14. DoD-attributable mortality rate (per 100,000 persons), 2015 to 2018

By comparing the maps, it is obvious that mortality related to DoD has been significantly expanding over time. In 2009, DoD-related mortality was concentrated primarily in some western states, as well as Oklahoma, Florida, and some counties of Virginia and Kentucky. By 2018, almost all US states have at least some counties with either orange or red color, reflecting the highest mortality levels from DoD.

Tables 6 to 8 present descriptive statistics for measures in all three sets of panel data, and tables 9 to 11 present the results of correlations between all measures of the analysis in these three sets of panel data.

Table 6. Descriptive Statistics of Measures for 2005-2009; N=3,107

Variable	Mean	S.D.	Min.	Max.
Age-Adj. DoD Mortality Rate	67.34	30.26	0.00	266.80
Black Population %	8.94	14.49	0.00	86.76
Hispanic Population %	7.55	12.82	0.00	98.63
Median Age	39.47	4.94	21.70	59.60
Population Change (per 1000)	-6.39	29.35	-783.37	156.00
Social Capital Index	0.00	1.39	-3.91	14.30
Married People %	56.38	6.73	27.49	93.59
Population Density (Log)	3.72	1.69	-2.12	10.78
Median Household Income (per $1000)	43.76	12.10	10.93	115.57
Unemployment Rate	6.57	2.23	1.67	21.03
Gini Index	0.43	0.04	0.21	0.64
People with College Education %	46.46	10.87	18.11	88.57
People under Poverty Line %	16.14	8.02	0.00	64.72

Table 7. Descriptive Statistics of Measures for 2010-2014; N=3,107

Variable	Mean	S.D.	Min.	Max.
Age-Adj. DoD Mortality Rate	82.33	35.28	0.00	318.40
Black Population %	9.08	14.55	0.00	85.91
Hispanic Population %	8.69	13.47	0.00	95.68
Median Age	40.75	5.20	21.60	64.50
Population Change (per 1000)	-10.41	43.60	-875.23	271.08
Social Capital Index	0.00	1.34	-3.93	17.44
Married People %	54.23	6.55	22.74	79.83
Population Density (Log)	3.75	1.70	-2.04	10.78
Median Household Income (per $1000)	46.35	11.93	19.15	123.97
Unemployment Rate	7.90	2.68	1.42	26.82
Gini Index	0.44	0.03	0.33	0.65
People with College Education %	50.11	10.65	21.35	87.89
People under Poverty Line %	16.85	6.51	1.04	47.92

Table 8. Descriptive Statistics of Measures for 2015-2019; N=3,107

Variable	Mean	S.D.	Min.	Max.
Age-Adj. DoD Mortality Rate	102.97	43.57	0.00	415.20
Black Population %	9.16	14.56	0.00	87.23
Hispanic Population %	9.46	13.93	0.00	99.17
Median Age	41.47	5.39	22.30	67.40
Population Change (per 1000)	-13.81	59.69	-1256.66	303.86
Social Capital Index	0.01	1.26	-3.18	21.81
Married People %	53.22	6.61	21.82	82.48
Population Density (Log)	3.75	1.71	-1.97	10.79
Median Household Income (per $1000)	53.29	14.09	21.50	142.30
Unemployment Rate	4.67	1.57	1.74	21.06
Gini Index	0.45	0.04	0.32	0.71
People with College Education %	52.74	10.68	6.28	91.62
People under Poverty Line %	15.14	6.31	2.43	55.45

Table 9. Pearson's r Correlation Matrix; 2005-2009; N= 3,107

	1	2	3	4	5	6	7	8	9	10	11	12	13
1. Age Adj. DoD Mortality	1	.09*	.11*	.00	-.02	-.35*	-.21*	.08*	.03	.27*	.01	-.19*	.02
2. Black Pop. %		1	-.11*	-.25*	-.01	-.32*	-.54*	.24*	.02	.31*	-.01	-.20*	-.05*
3. Hispanic Pop. %			1	-.28*	-.20*	-.27*	-.05*	-.06*	-.00	-.07*	-.01	-.01	.02
4. Median Age				1	.19*	.47*	.49*	-.41*	-.04*	-.05*	.02	-.10*	.03
5. Pop. Change					1	.15*	.05*	-.30*	.03	.01	-.01	-.24*	-.04*
6. Social Capital						1	.34*	-.34*	-.05*	-.42*	-.01	.34*	.04*
7. Married People %							1	-.38*	.01	-.28*	.04*	.04*	.01
8. Pop. Density (log)								1	.01	.18*	-.04*	.23*	-.03
9. Median Income									1	-.03	-.43*	-.09*	-.75*
10. Unemployment %										1	.03	-.40*	.01
11. Gini Index											1	.02	.60*
12. College Edu. %												1	.10*
13. Below Poverty Line %													1

*= p<.05

Table 10. Pearson's r Correlation Matrix; 2010-2014; N= 3,107

	1	2	3	4	5	6	7	8	9	10	11	12	13
1. Age Adj. DoD Mortality	1	.07*	.09*	.03	.01	-.26*	-.17*	.06*	-.31*	.36*	.15*	-.22*	.31*
2. Black Pop. %		1	-.11*	-.22*	-.02	-.19*	-.57*	.24*	-.25*	.40*	.36*	-.21*	.47*
3. Hispanic Pop. %			1	-.31*	-.23*	-.24*	-.08*	-.05*	.04*	-.02	.12*	-.02	.10*
4. Median Age				1	.20*	.47*	.45*	-.40*	-.11*	.01	-.13*	-.10*	-.26*
5. Pop. Change					1	.19*	.06*	-.33*	-.26*	.00	-.05*	-.25*	.09*
6. Social Capital						1	.29*	-.43*	.11*	-.44*	-.10*	.29*	-.36*
7. Married People %							1	-.34*	.31*	-.38*	-.47*	.09*	-.58*
8. Pop. Density (log)								1	.32*	.19*	.11*	.22*	-.03
9. Median Income									1	-.45*	-.35*	.67*	-.75*
10. Unemployment %										1	.21*	-.41*	.57*
11. Gini Index											1	-.07*	.54*
12. College Edu. %												1	-.51*
13. Below Poverty Line %													1

*= p<.05

Table 11. Pearson's r Correlation Matrix; 2015-2019; N= 3,107

	1	2	3	4	5	6	7	8	9	10	11	12	13
1. Age Adj. DoD Mortality	1	.06*	.07*	.08*	.03	-.23*	-.18*	.10*	-.26*	.32*	.18*	-.22*	.26*
2. Black Pop. %		1	-.11*	-.19*	-.02	-.16*	-.56*	.24*	-.26*	.33*	.39*	-.19*	.44*
3. Hispanic Pop. %			1	-.32*	-.22*	-.19*	-.10*	-.04*	.05*	.04*	.05*	-.06*	.08*
4. Median Age				1	.18*	.36*	.41*	-.36*	-.12*	.05*	-.08*	-.08*	-.22*
5. Pop. Change					1	.15*	.05*	-.34*	-.29*	.07*	-.05	-.25*	.11*
6. Social Capital						1	.29*	-.40*	.08*	-.35*	-.14*	.28*	-.33*
7. Married People %							1	-.32*	.33*	-.37*	-.48*	.15*	-.59*
8. Pop. Density (log)								1	.36*	.02	.15*	.24*	-.06*
9. Median Income									1	-.47*	-.36*	.67*	-.74*
10. Unemployment %										1	.33*	-.44*	.59*
11. Gini Index											1	-.11*	.57*
12. College Edu. %												1	-.54*
13. Below Poverty Line %													1

*= p<.05

The correlation matrices show associations in 2014 and 2019 that are more similar, generally speaking, than associations in 2009. For example, while the Gini index and “below poverty line percentage” have a positive significant correlation with mortality caused by DoD in 2014 and 2019, the correlation between the same measures is insignificant in 2009. In all three years, Black and Hispanic county population percentage, population density, and unemployment percentage have positive correlations with mortality. Conversely, social capital, college education, and median income have negative correlations with mortality. Population change has a statistically insignificant correlation (i.e., there is no evidence that *r* is different from 0.0) with mortality in all three years.

Tables 12 and 13 show the results of regression models. In these models, demographic measures serve as control variables; social and economic measures are the main predictor variables, based on the theory of DoD and other studies, as discussed in introduction chapter. In both non-spatial and spatial models, models one and two, include, respectively, (1) demographic and (2) social and economic measures. Model three includes all measures, showing how much of the social and economic effect is actually attributable to demographic changes within counties over time.

According to table 12, which presents the results of non-spatial fixed-effect panel models, changes in DoD-attributable mortality are significantly associated with changes in most of the measures across time. In model three, increases in Hispanic population percentage ($\beta = 2.78$, $p < 0.001$), median age ($\beta = 2.78$, $p < 0.001$), median income per thousand dollars ($\beta = 0.28$, $p < 0.001$), percentage of population with a college education ($\beta = 1.67$, $p < 0.001$), and percentage of population under the poverty line ($\beta = 0.48$, $p < 0.001$) all significantly contribute to higher DoD-related

Table 12. Non-spatial panel fixed-effect regression models predicting changes in age-adjusted DoD-attributable mortality; N=3107

Variable	Model 1 Est. (S.E.)	Model 2 Est. (S.E.)	Model 3 Est. (S.E.)
Demographic Measures			
Black %	1.32 (.345)***		.32 (.326)
Hispanic %	4.94 (.210)***		2.78 (.225)***
Median Age	5.38 (.199)***		2.78 (.211)***
Population Change (per 1000)	.01 (.021)		.03 (.021)
Social and Economic Measures			
Social Capital Index		-.105 (.795)	-2.42 (.790)**
Married People %		-1.68 (.115)***	-1.22 (.117)***
Pop. Density (log)		-22.40 (6.793)***	-36.05 (.175)***
Median Income (per $1000)		.40 (.045)***	.28 (.045)***
Unemployment %		-2.46 (.186)***	-2.12 (.183)***
Gini Index		19.30 (11.830)	5.48 (11.616)
With College Edu. %		2.27 (.096)***	1.67 (.101)***
Under Poverty Line %		.55 (.086)***	.48 (.084)***
AIC	90257.86	89411.46	88955.75

*= p<.05; **= p<.01; ***= p<.001

mortality. Conversely, decreases in social capital ($\beta = -2.42$, $p < 0.01$), the percentage of married people ($\beta = -1.22$, $p < 0.001$), the log of population density ($\beta = -36.05$, $p < 0.001$), and unemployment ($\beta = -2.12$, $p < 0.001$) are associated with significant increases in mortality caused by DoD. For example, one percent increase in Hispanic population in a county over time is associated with 2.78 more deaths related to DoD per 100,000 residents. Similarly, one percent increase in the married population of a given county is associated with 1.22 fewer deaths caused by DoD per 100,000 persons.

One interesting point is that while income and percentage with a college education have significant negative correlations with DoD-related mortality, the associations of the same variables in regression models becomes significantly positive. On the other hand, while unemployment and population density have a significant positive correlation with mortality, in regression panel models their effects are significantly negative. Those points deserve more attention and we will come back to them in the next chapter.

Table 13 shows the results of SLX panel models which are spatial. The coefficient of spatially lagged measures (the rows with factor "W") represent the indirect effects of predictor variables, which capture the spatial effects of predictor variables in neighboring counties. In comparison to the effects of predictors in non-spatial models, the direct effects of predictor variables in spatial models are the same in terms of significance, and the magnitude of coefficients is very close. In model three, a rise in Hispanic population percentage ($\beta = 2.85$, $p < 0.001$), median age ($\beta = 2.81$, $p < 0.001$), median income ($\beta = 0.28$, $p < 0.001$), percentage of population with a college education ($\beta = 1.67$, $p < 0.001$), and percentage of population under the poverty line ($\beta = 0.56$, $p < 0.001$) is associated with a significant increase in mortality caused by DoD. At the same time, a decrease in social capital ($\beta = -2.13$, $p < 0.01$), percentage of married people ($\beta = -1.23$, $p < 0.001$), log of population density ($\beta = -36.23$, $p < 0.001$), and unemployment ($\beta = -2.12$, $p < 0.001$) across time is associated with a significant reduction in DoD-related mortality. For instance, a one-year increase in the median age of a county over time is associated with 2.81 more deaths related to DoD, per 100,000 persons. Conversely, a one percent increase in population density over time is associated with .36 fewer deaths caused by DoD, per 100,000 residents.

Table 13. SLX panel fixed-effect regression models predicting changes in age-adjusted DoD-attributable mortality; N= 3107

Variable	Model 1 Est. (S.E.)	Model 2 Est. (S.E.)	Model 3 Est. (S.E.)
Demographic Measures			
Black %	1.33 (.345)***		.35 (.327)
Hispanic %	4.91 (.211)***		2.85 (.226)***
Median Age	5.33 (.201) ***		2.81 (.212)***
Population Change (per 1000)	.01 (.021)		.02 (.021)
W* Black %	-.00 (.042)		-.11 (.050)*
W* Hispanic %	-.10 (.041)*		.00 (.045)
W* Median Age	-.00 (.140)		.32 (.148)*
W* Population Change (per 1000)	-.06 (.017)***		-.03 (.018)
Social and Economic Measures			
Social Capital Index		-.10 (.799)	-2.13 (.798)**
Married People %		-1.70 (.115)***	-1.23 (.118)***
Pop. Density (log)		-22.28 (6.833)**	-36.23 (7.200)***
Median Income (per $1000)		.40 (.045)***	.28 (.045)***
Unemployment %		-2.49 (.189)***	-2.12 (.188)***
Gini Index		19.86 (11.846)	6.15 (11.622)
With College Degree %		2.27 (.097)***	1.67 (.102)***
Under Poverty Line %		.56 (.086)***	.49 (.084)***
W* Social Capital Index		.87 (.575)	.91 (.619)
W* Married People %		.04 (.112)	-.07 (.125)
W* Pop. Density (log)		.76 (.465)	1.09 (.501)*
W* Median Income (per $1000)		-.00 (.076)	-.04 (.076)
W* Unemployment %		.01 (.205)	.31 (.201)
W* Gini Index		-17.68 (23.559)	-37.45 (24.004)
W* With College Edu. %		-.06 (.070)	-.16 (.072)*
W* Under Poverty Line %		-.02 (.161)	.18 (.158)
AIC	90242.38	89417.86	88944.73

*= p<.05; **= p<.01; ***= p<.001

Among the spatial spillover effects, an increase in the log of population density (θ = 1.09, $p < 0.05$) and median age (θ = .03, $p < 0.05$) in a given county over time significantly contributes to the rise of DoD-related mortality in the neighboring counties, and on the other hand, a decline in Black population percentage ($\theta = -0.11$, $p < 0.05$) and percentage of population with a college education ($\theta = -0.16$, $p < 0.05$) in a county across time contributes significantly to mortality caused by DoD in neighboring counties. For example, one year rise in median age of a county over time is associated with .31 more deaths caused by DoD per 100,000 residents in neighboring counties.

One noticeable point is the opposite significant association of the direct and indirect effect of population density and college education percentage on the mortality of neighboring counties. While a rise in population density of a county across time is associated with fewer despair deaths in the same county, it is also associated with more deaths caused by despair in neighboring counties. Also, an increase in the percentage of people with a college education in a county over time is associated with more despair deaths in the same county, but it is associated with fewer despair deaths in adjacent counties.

CHAPTER V

DISCUSSION

The mortality of midlife non-Hispanic white people caused by drug, alcohol, and suicide, which are collectively referred to as deaths of despair (DoD), has significantly increased in recent decades. The increase in DoD is one of the main reasons for stagnancy in the life expectancy of Americans. In this study, I addressed two gaps in the existing literature on that issue. The first gap is that the spatial distribution of DoD-related mortality growth in the US is not well understood. To address this shortcoming, I analyzed mortality trends that are attributable to drugs, alcohol, and suicide, from 1999 to 2019, in all 50 states. I started the analysis with a general look at DoD-related mortality trends in the US. Results from this study show that there is a significant increase in all three causes of death (i.e. drugs, alcohol, and suicide) since 1999. This finding is contrary to other studies (e.g. Ruhm 2018a; Masters et al. 2017 and 2018) that have emphasized only the rise in drug-related mortality. At the same time, it is equally clear that, in terms of both level and growth, the situation for drug mortality is more critical.

The general uptrend for the whole country should not mislead us that the situation is similar for all regions, however. As the results show, there are significant disparities across states in terms of the level and growth of mortality caused by DoD. For example, while drug mortality has recently grown with an annual rate near 20 percent for states such as New Jersey, North Dakota, and Maryland, in other states like Wyoming and Utah the growth is essentially zero. In the case of Hawaii, the growth in drug mortality is actually negative. In another example of DoD disparities across states, alcohol-related mortality in Nebraska is increasing by about 9 percent per year, but Louisiana and Hawaii are improving—i.e., growth is negative. Although the range of changes in suicide mortality is narrower across states, there are nevertheless notable differences between states like Nebraska with about five percent growth and Arizona with negative growth.

Another point to consider is that high mortality growth in one specific cause of DoD does not mean high growth in the other causes. For instance, although Utah is among the states with the lowest growth in terms of drug and alcohol mortality, its growth in suicide mortality is among the highest. As another example, Florida has one of the highest growth rates with respect to drug-related mortality but its suicide mortality growth rate is near zero.

One issue that makes the analysis of disparities more complex is the significant difference between the distribution of mortality level and growth, as figure 4 , 5, 7, 8, 10, and 11 clearly show. For example, in terms of drug mortality, North Dakota is among the states experiencing the highest rate of growth, but in terms of mortality level, it is among the lowest. Similarly, while Nevada, Arizona, New Mexico, and Oklahoma are among the states with the highest growth in suicide mortality, their suicide mortality levels are among the lowest. Of course, some states, like Florida (for drug), West Virginia (for drug and alcohol), and Utah (for suicide) do exhibit both high growth and high levels of mortality—and these states are of special concern. Therefore, it is imperative to differentiate between level and change in DoD-attributable mortality when discussing the public health situation in any given state.

Figure 15 shows hot-spot states in terms of growth for all three causes of DoD. If we define a hot-spot state one with DoD growth of 10 percent or higher, all five of those states (Maryland, Connecticut, New Jersey, Delaware, and New Hampshire) are located in the Northeast region. This issue deserves serious additional investigation. At the first look, the bias of small area estimation may be a concern as most of those states are among the smallest states. However, that is not the case because the lowest deaths count caused by despair among those five states is for Delaware, which annually has been around 500 deaths in recent years. That number is big enough to refute concerns about small-sample bias. A possible explanation is related to education, as the majority of those states are among the most educated in the U.S. Although counterintuitive, one line of reasoning is that a heavier burden of distress and frustration falls on midlife white people with low education in states that are

Figure 15. States with highest growth (10 percent or above) of despair deaths

above average with respect to educational attainment. Results from my regression models are consistent with that explanation; I will return to this point momentarily.

The second literature gap addressed by this study is to find a set of factors that may explain increases in county-level DoD. As discussed in the previous chapter, the results of non-spatial and spatial panel models are consistent. In these models, a rise in measures related to social context such as social capital and the percentage of married people over time is associated with reductions in the level of despair-related mortality. This result is consistent with some previous studies (e.g. Zooroba and Salemi 2017, Monnat 2018). If we consider that growth in those measures is likely associated with reductions in social isolation, then my results are consistent with the argument of DoD theory that social isolation is one of the main causes of despair-attributable mortality. In addition, over time, there is an association between an increase in the percentage of the Hispanic population of a county and higher mortality caused by despair. As I discussed in the first chapter, some studies (e.g. Pickett and Wilkinson 2008; Osypuk et al. 2009; Osypuk et al. 2010) address how shared culture and strong communal relationships create Hispanic enclaves. Those ethnic enclaves provide support and benefits for the Hispanic residents but, on the other hand, it can be argued that ethnic enclaves cause more isolation of the vulnerable local white population, and the results support that argument.

Among economic variables, an increase in the percentage of people under the poverty line is significantly associated with higher DoD over time. That result is expected and is consistent with the theory of DoD, which asserts that economic hardships are among the chief determinants of DoD. Also, a rise in the population density of a county is significantly associated with fewer DoD. If we consider the increase in population density as an indication of the economic prosperity of the county (Nunn et al. 2018), that result would be consistent with the theory of DoD as well.

However, there are three socioeconomic status (SES)-related measures with counterintuitive associations that apparently do not support the DoD argument, including median income, percentage of people with a college education, and unemployment. Per the DoD theory, I hypothesized that counties experiencing a rise in median income, percentage of people with a college education, and employment will experience less DoD. However, the regression models show just the opposite; DoD-related mortality was *higher* in counties that experienced these seemingly salubrious shifts in socioeconomic conditions. Returning to my prior argument, one plausible explanation for this unexpected result involves subjective socioeconomic status (SES); there is a well-established literature promoting the argument that subjective SES is as important as, or even outweighs, objective SES with respect to health outcomes (e.g. Singh-Manoux et al. 2003; Singh-Manoux et al. 2005; Demakakos et al. 2008; Wolff et al. 2010; Gelatt 2013; Cundiff et al. 2013; Euteneuer 2014; and Krug and Eberl 2018). Therefore, white individuals with lower education living in counties with increasing average income, education, and employment likely struggle with more psychological distress and pain than poorly-educated whites in other areas, because they compare their SES with people who enjoy much higher standards of living.

Other analyses also support this line of reasoning. For instance, Siddiqi et al. (2019) emphasize the perception among whites that their social status is being threatened as a contributor to premature mortality. Case and Deaton (2015, 2017, and

2020) look at subjective SES from another angle. They argue that white baby boomers with low education and traditional manufacturing job skills compare their life situation to their parents' lives. Since many baby boomers cannot meet or exceed the living standard that they were accustomed to as children, they feel distressed and frustrated. As Woolf and Schoomaker (2019) assert, there are other works based on ethnography and qualitative methods that emphasize perceived loss of social status and uncertainties of the future as causes of distress and hopelessness among working-class whites (e.g. Lamont 2009; Putnam 2015; Gest 2016; Hochschild 2018; Metzl 2019).

To my knowledge, this study is one of the few to inspect DoD by longitudinal models. If the arguments on how the working-class whites' perception of their SES causes extra dismay and pain are true, that would show one of the substantial strengths of longitudinal models applied in this analysis over the conventional cross-sectional models applied in most studies. Generally speaking, the findings of this study can be interpreted as confirmation for the theory of DoD. However, the results suggest some direction for future studies.

First of all, further studies are needed to shed light on the spatial aspects of DoD. As figure 4.1 to 4.3 in the last chapter show, there are significant DoD disparities across states and counties. I suggest new analyses to focus more on local explanations, instead of a single general explanation approach used in this study. Indeed, one important implication of this study is that local analyses of DoD could help explain why, for example, alcohol-related mortality is predominant in one region but suicide is predominant in another. This point is critical to make new, more effective policies capable of addressing DoD because each region is struggling with its own set of specific problems.

In addition, future studies are necessary to explore the role of significant spillover effects. Model results highlight four measures that are spatially associated with despair-related mortality in neighboring counties, including Black population percentage, median age, population density, and percentage of the population with a college education. One noticeable point is the opposite association of population density and despair mortality within and across counties. The spillover effects suggests an increase in population density over time is associated with higher despair mortality in neighboring counties. As I discussed, higher population density can be an indication of economic prosperity in a county (Nunn et al. 2018). In addition, counties are self-governing entities that implement their own social and health policies as well as development programs (Knapp et al. 2019; Osypuk and Galea 2007; National Association of Counties 2016). So each county provides its own benefits for its residents, but that is not necessarily the case for the residents of neighboring counties. We may argue that the prosperity of a county over time has a negative influence on the subjective SES of residents in neighboring counties who may not enjoy that same level of prosperity. This is additional evidence that could underscore the importance of perceived SES; however, future studies are needed to examine that issue with stronger and more direct evidence.

The percentage of people with college education is another measure that has an opposite within- and across-county effect. Among the other SES-related covariates, including income and employment, college education is the only one with such an opposite significant effect. That issue seems complex and further studies are necessary. In addition, although there is no significant spillover effect of social capital on mortality caused by despair in this analysis, using the same social capital index, Yang et al. 2019 argue how a higher level of social capital in a county significantly reduces mental distress, not only within the county, but also in neighboring counties. A future analysis that replicates their study for specifically midlife whites would be insightful.

The second direction for future studies is to take additional factors into account. For example, new studies can compare how despair-related mortality varies between different racial/ethnic groups. Attention to midlife Blacks and Hispanics is particularly important because, as discussed in chapter one, there is an uptrend in mortality caused by drugs, alcohol, and suicide for those groups since 2010. Another factor that is substantial but not included in this study is sex. There are studies that point to disparities in DoD between white males and females (Gelamn and Auerbach 2016; Woolf et al. 2018; Masters et al. 2017 and 2018). Because the main goal of this study is to find a general explaination for DoD, I did not take sex into account; however, future studies that inspect the role of sex could be insightful. Also, analyses comparing the mortality of white people with and without a college education would be helpful. A stronger focus on job market conditions and different types of occupations is another suggestion to help refine research in this area of inquiry.

Third, future studies could evaluate the influence that each cause of death has on life expectancy. For example, applying methods such as life tables and age and cause decomposition of differences in life expectancy can evaluate the weight of each cause of death for each age group, and therefore help refine some findings from this analysis. As an example for applying such methods, Roberts et al. (2020) analyze the effect of different causes of deaths on life expectancy gap between whites and Blacks in Washington DC.

Limitations

Despite its many notable strengths, there are also limitations to this study. Perhaps the most problematic issue is what is called the ecological fallacy. Despair-related death is a phenomenon happening at the individual level; however, in this analysis, we focus on factors measured at the county level. The fact that we equally attribute the social and economic measures like social capital, median income, or poverty of a county to all deaths that happened in that county can be a matter of debate.

Another important limitation of this study pertains to the potential pitfalls of applied fixed-effect panel models. As discussed in the methods chapter, one of the strengths of applied fixed-effect models is to account for the unobserved time-invariant county heterogeneity. However, in reality, there are always some time-varying unobserved factors as well. Alcohol tax, drug availability, and drug prices are examples of three important variables that I was unable to include in the models. For instance, Naimi et al. (2018) discuss how state-specific excise taxes experience substantial inflation-adjusted declines over time, which could relate to alcohol consumption at the state level. Unick et al. (2014) argue that heroin market dynamics in the US, like price, influence heroin overdoses. These measures are unobserved in my data, vary over time, and therefore have the potential to confound associations observed in the fixed-effect regression models.

Furthermore, regression estimates from fixed-effect models are based on changes within counties over time, so such models are not able to capture the effect of any measure that does not change, or slowly changes, over time. The Gini index can potentially be one of those measures. The mean of the Gini index in three data sets of panel data is .43, .44, and .45, respectively for 2009, 2014, and 2019, which suggests a very slow increase of income inequality across time. Although the estimation suggests that an increase in the Gini index (i.e. increase in income inequality) of a county over time is associated with higher mortality caused by despair, that association is not statistically significant. Also, as discussed in the methods chapter, another potential issue of fixed-effect models is reverse causality. Although it seems that mortality, as the final outcome measure in any model involving human beings, cannot affect social and economic predictors, we need to consider the fact that despair mortality is the outcome of distress, pain, and health deterioration, which could simultaneously influence main predictors (e.g., marital and employment status) in my models. So one needs to be cautious during the interpretation of coefficients as causal effects unless there is very strong empirical evidence for that.

Policy suggestions

Although providing detailed policies is beyond the scope of this study, the findings do suggest some interesting directions for future policy. Of course, each state can impose policies on drugs and alcohol use such as prescription regulations or alcohol tax, to reduce the use of drugs and/or alcohol, depending on the severity of the problem in the state. However, to take a step toward the social determinants of health and a deeper understanding of the problem, focusing to a greater extent on vulnerable white people is essential. Instead of the common stereotypical language that says "whites are doing better than Blacks or Hispanics," we need more accurate language acknowledging the fact that some specific groups of white Americans are struggling with life hardships like other vulnerable racial/ethnic or marginalized groups, and perhaps even harder in some respects because they have to endure the extra burden of perceived loss of SES.

Also, as the theory of deaths of despair argues and the findings confirm, the role of education is critical, so policies that encourage higher education seem warranted. In addition, investment in supporting communities and promoting engagement in religious, political, sport, entertainment activities, etc. can work against social isolation. As other studies (e.g. Woolf and Schoomaker 2019; Jonas et al 2019) suggest, policies strengthening the capacity of the healthcare system to deal with chronic diseases, and more focus on behavioral health services are considerable. Moreover, if the findings of this study concerning the importance of perceived SES were true, strategies to correct or improve the perception of suffered individuals would be helpful, and the field of psychology can provide valuable advice. Obviously, all of those suggested policies should be tailored according to the major local problems.

The stagnancy of Americans' life expectancy should be considered a serious priority for all US citizens, especially policymakers and political authorities. The findings of this dissertation confirm that deaths of despair are at least one of the main culprits for that issue. Substantial geographical disparities in DoD are among the most important findings, and instead of a general simple approach, the policies to address the issue should take local considerations into account. In addition, social isolation and economic hardships are other factors emphasized in the theory of DoD and confirmed by this study. The significant role of subjective socioeconomic status and perception of vulnerable whites of themselves compared to stereotypical “privileged whites” is another major finding of this study and further studies particularly can focus in that direction and provide more insight.

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APPENDICES

Appendix A. ICD-10 codes

Table 14 presents the ICD-10 codes for deaths of despair. All codes except for F11-16, F19, and F10 are consistent with Case and Deaton's (2015) original study. I added those extra codes based on Masters et al. (2018). They argue that F11-16 and F19 are related to drug dependency and abuse, making a more comprehensive set of ICD codes for drug-related deaths. Likewise, adding F10 for alcohol-dependence disorders better captures the full range of alcohol-related deaths.

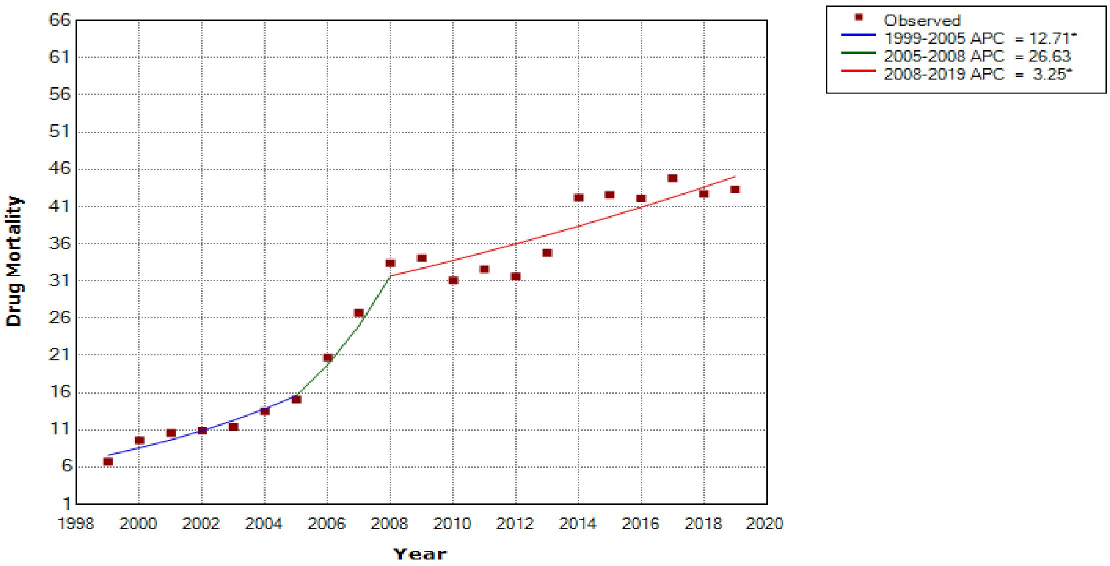
Table 14. ICD-10 Codes for despair mortality

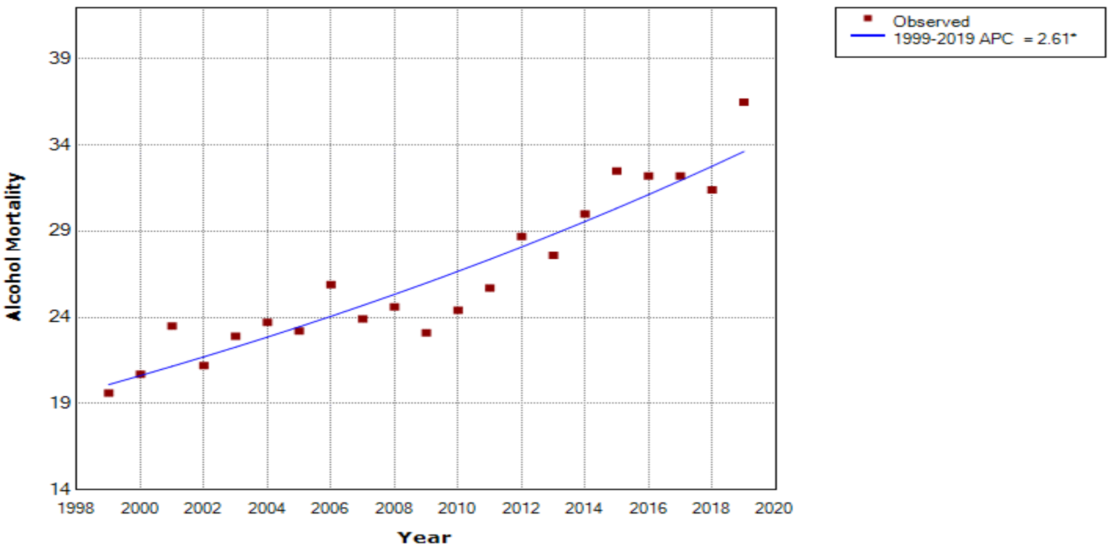
Cause	Codes
Drug	F11-16, F19, X40-X45, X85, Y10-Y15
Alcohol	F10, K70, K73-K74
Suicide	U03, X60-X84, Y87

Appendix B. mortality trends in states

Figure 16 to 65 present trends of despair-related mortality in 25-64-year-old age group of whites for all 50 states. There are three graphs for each state on each page, showing mortality trends attributable to drugs, alcohol, and suicide, respectively, from 1999 to 2019.

Figure 16. Trends of DoD in Alabama





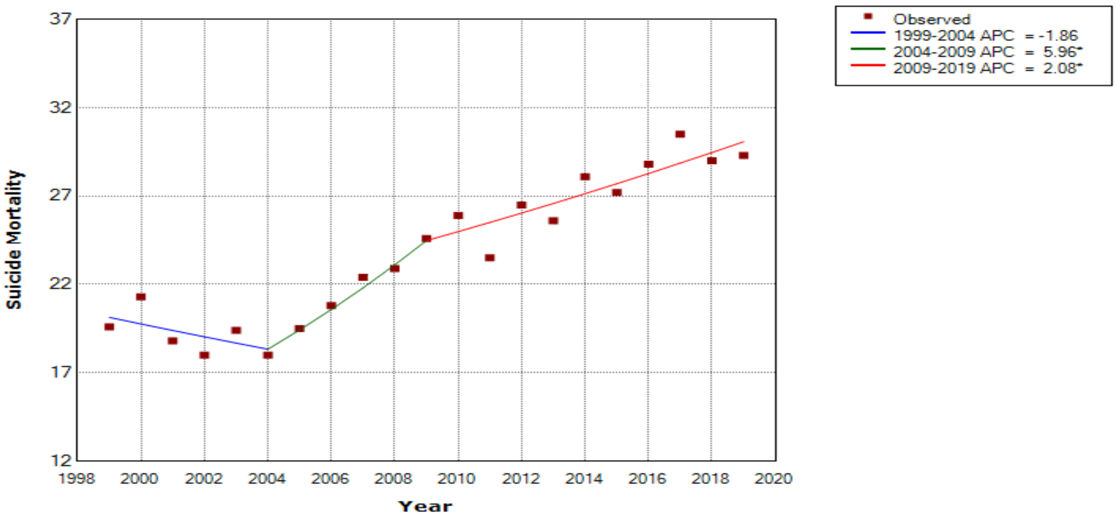


Figure 17. Trends of DoD in Alaska

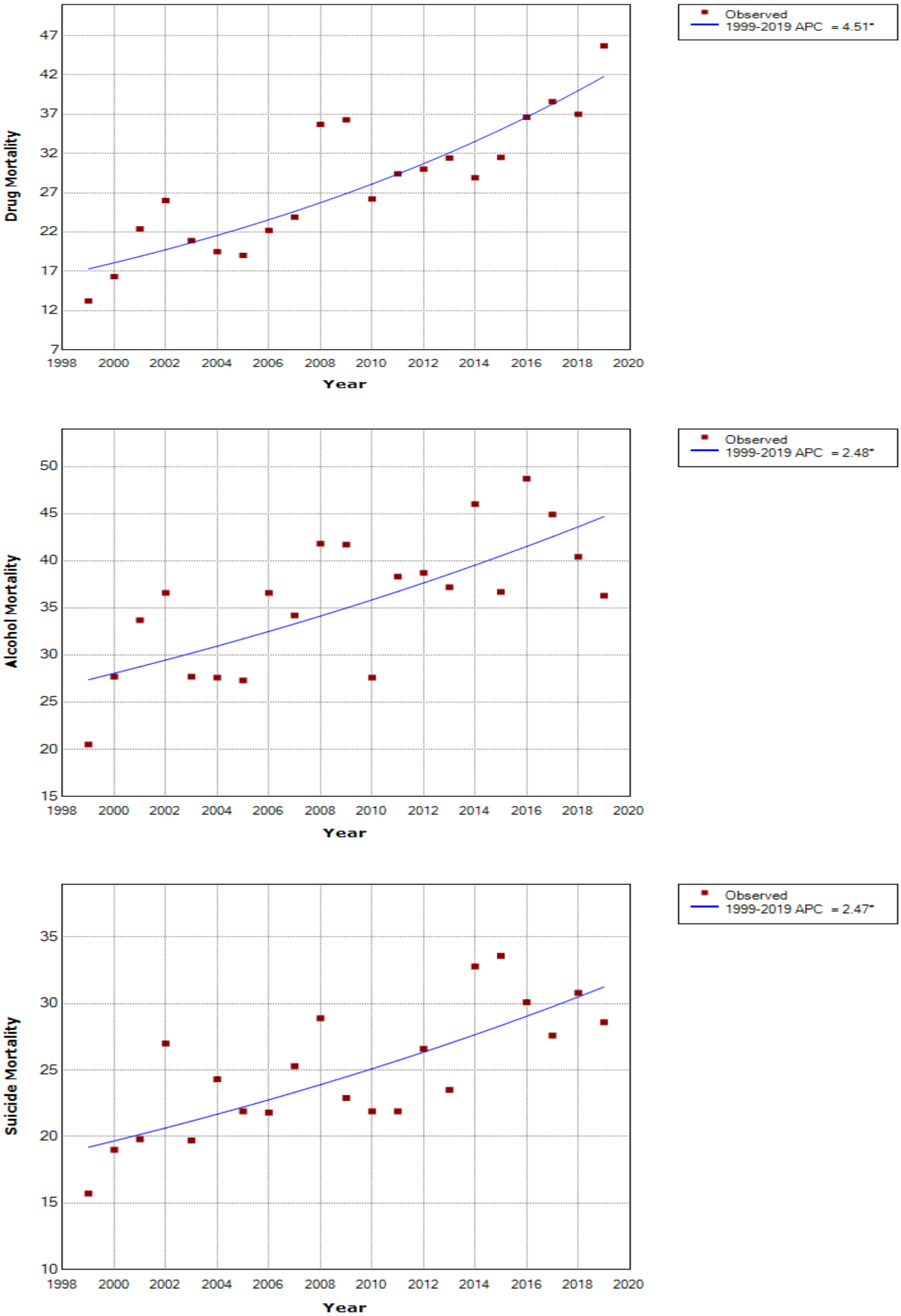
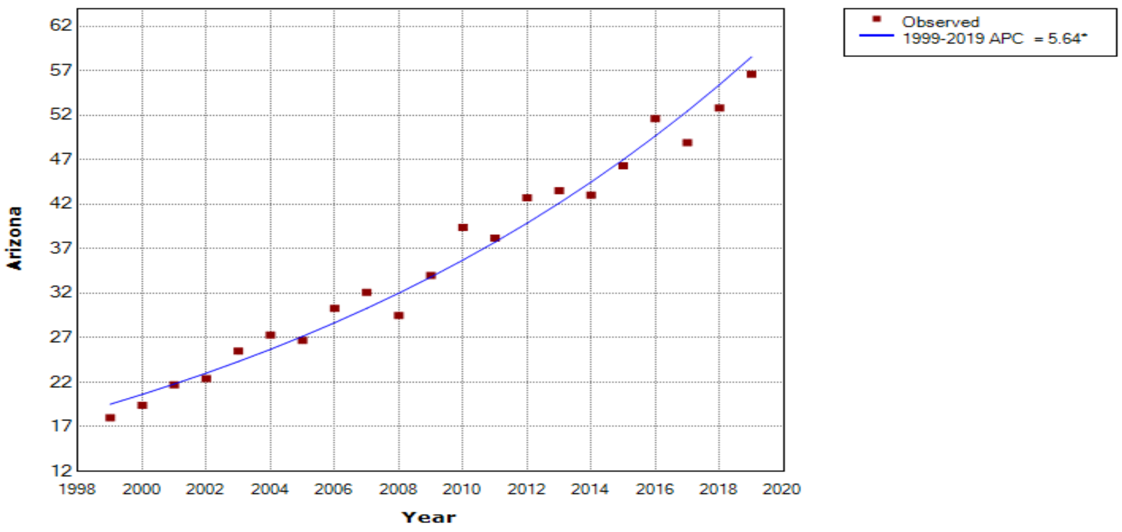
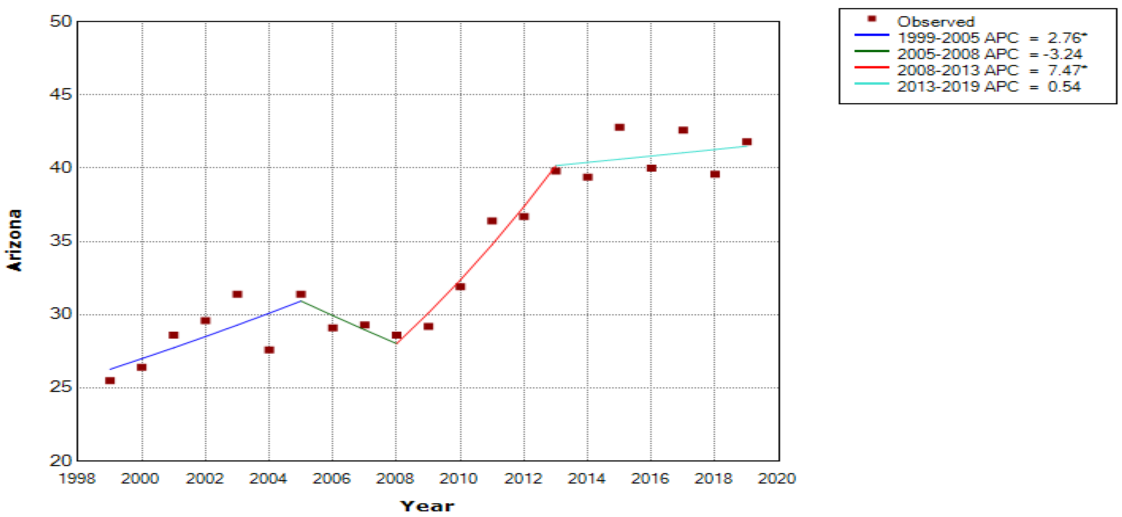


Figure 18. Trends of DoD in Arizona





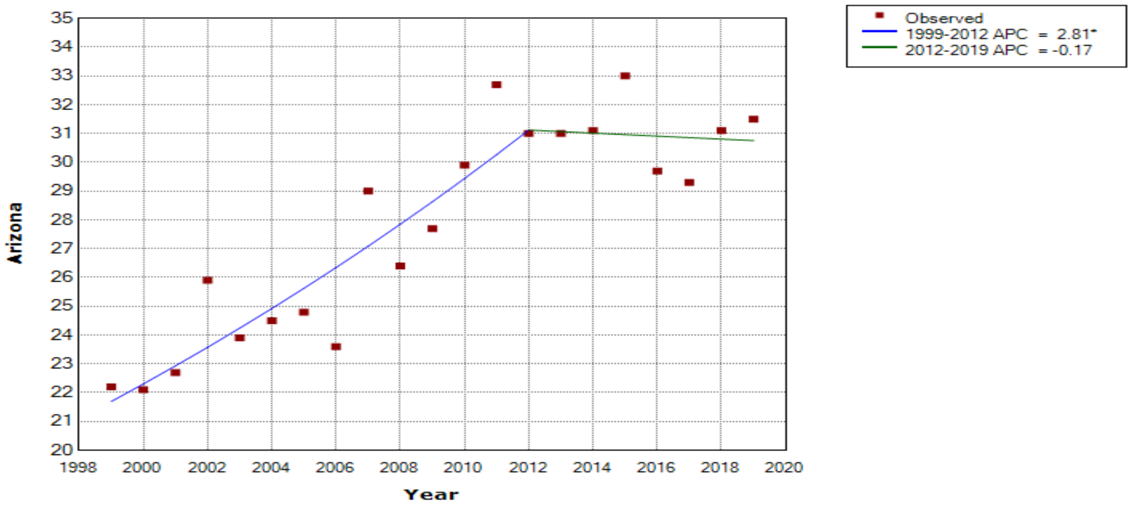
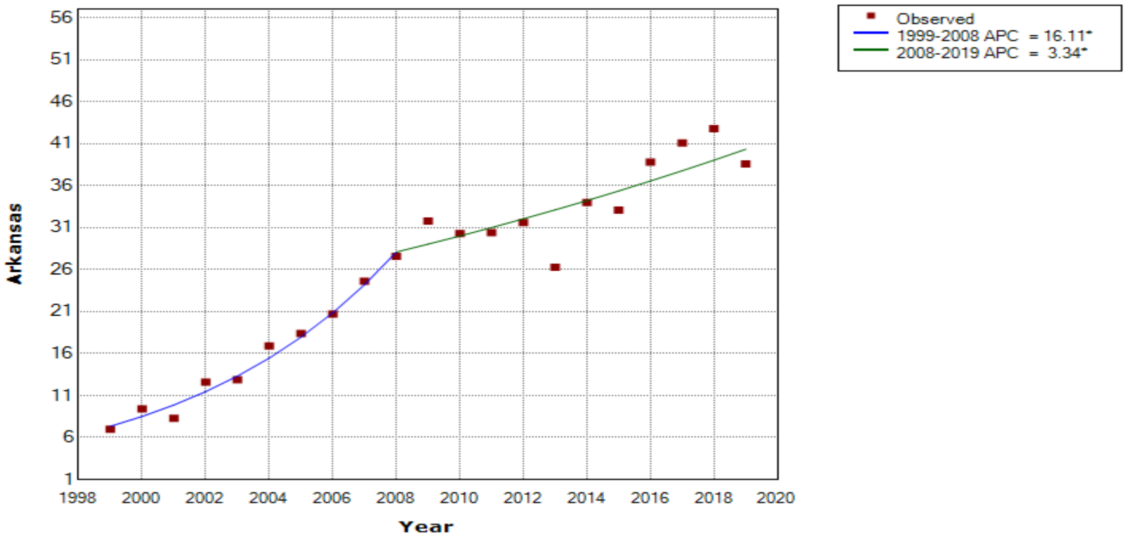
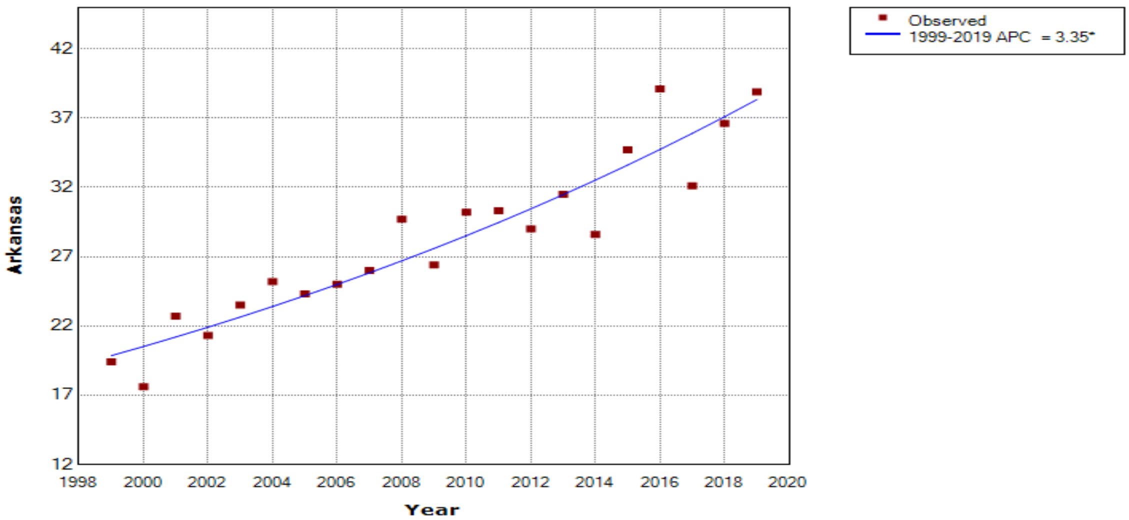


Figure 19. Trends of DoD in Arkansas





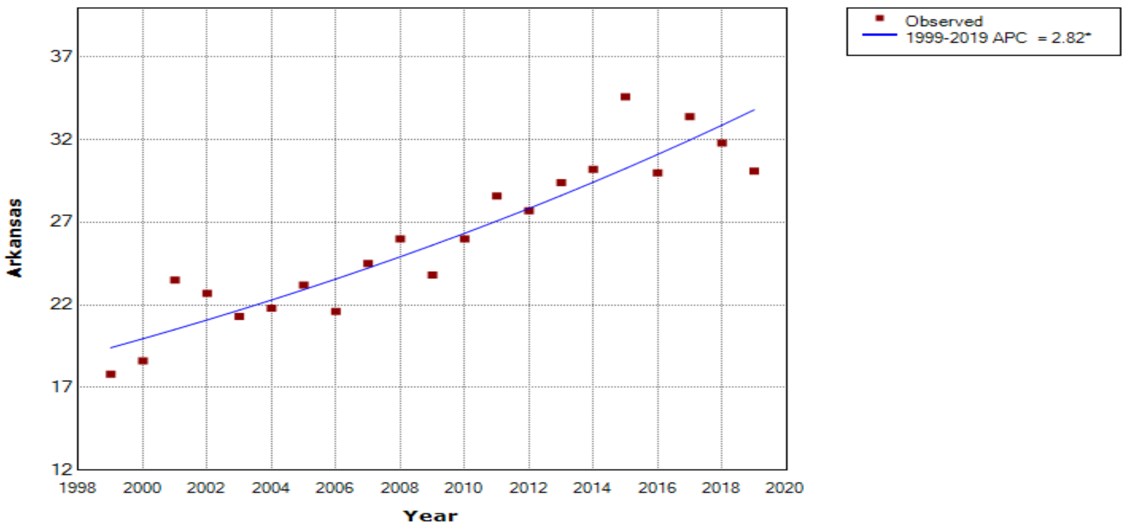


Figure 20. Trends of DoD in California

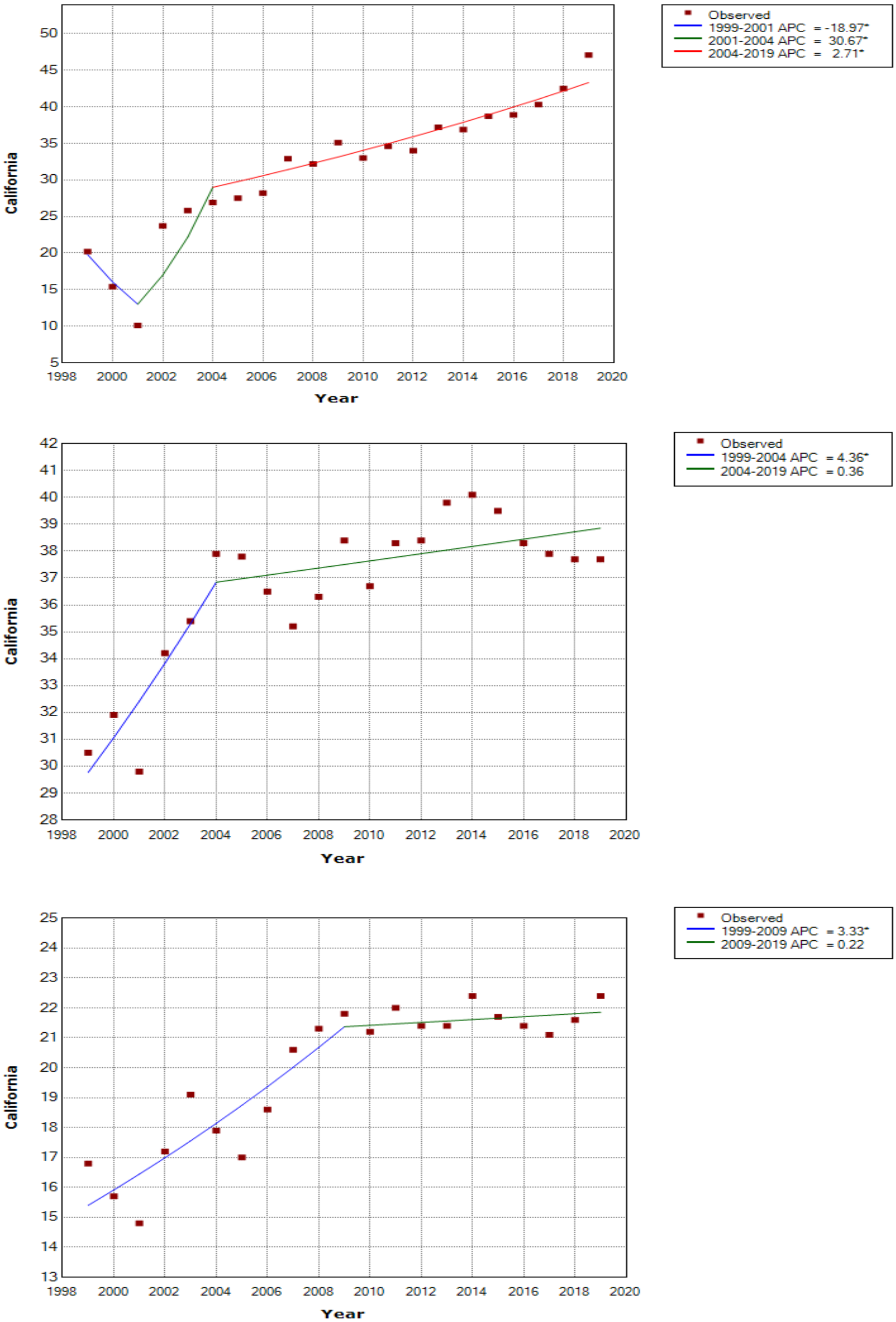
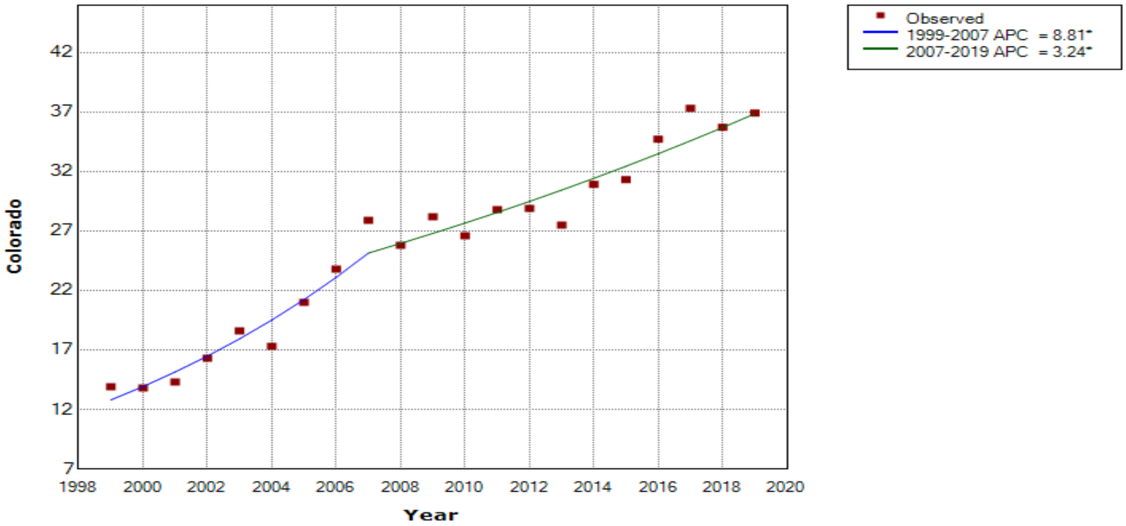
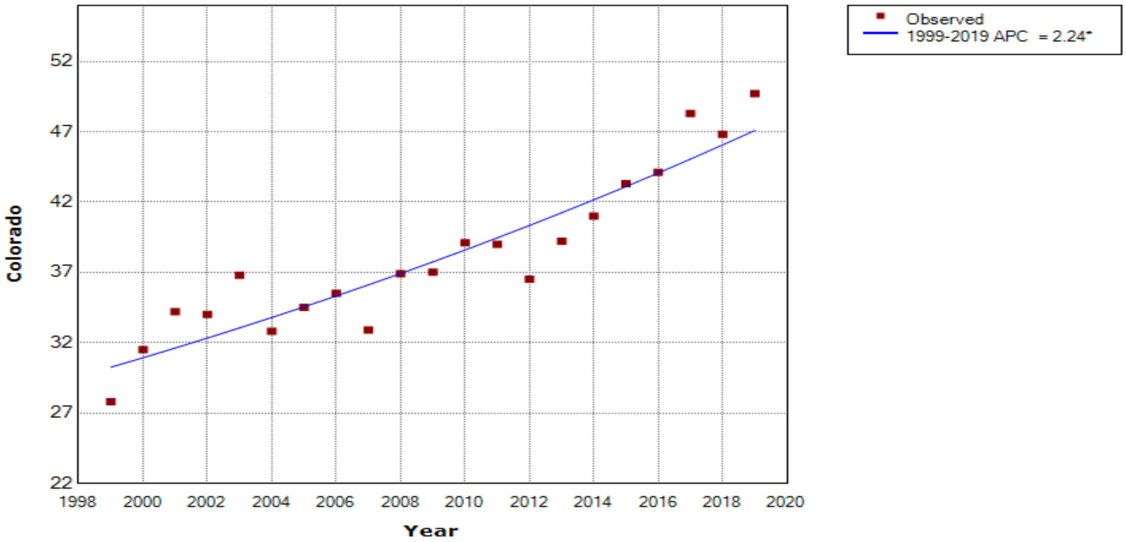


Figure 21. Trends of DoD in Colorado





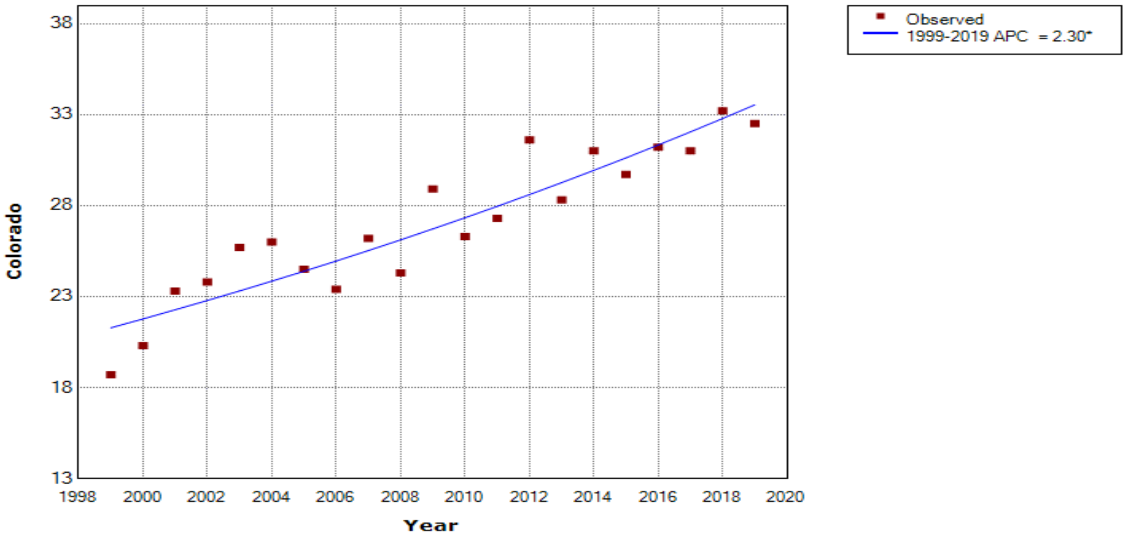


Figure 22. Trends of DoD in Connecticut

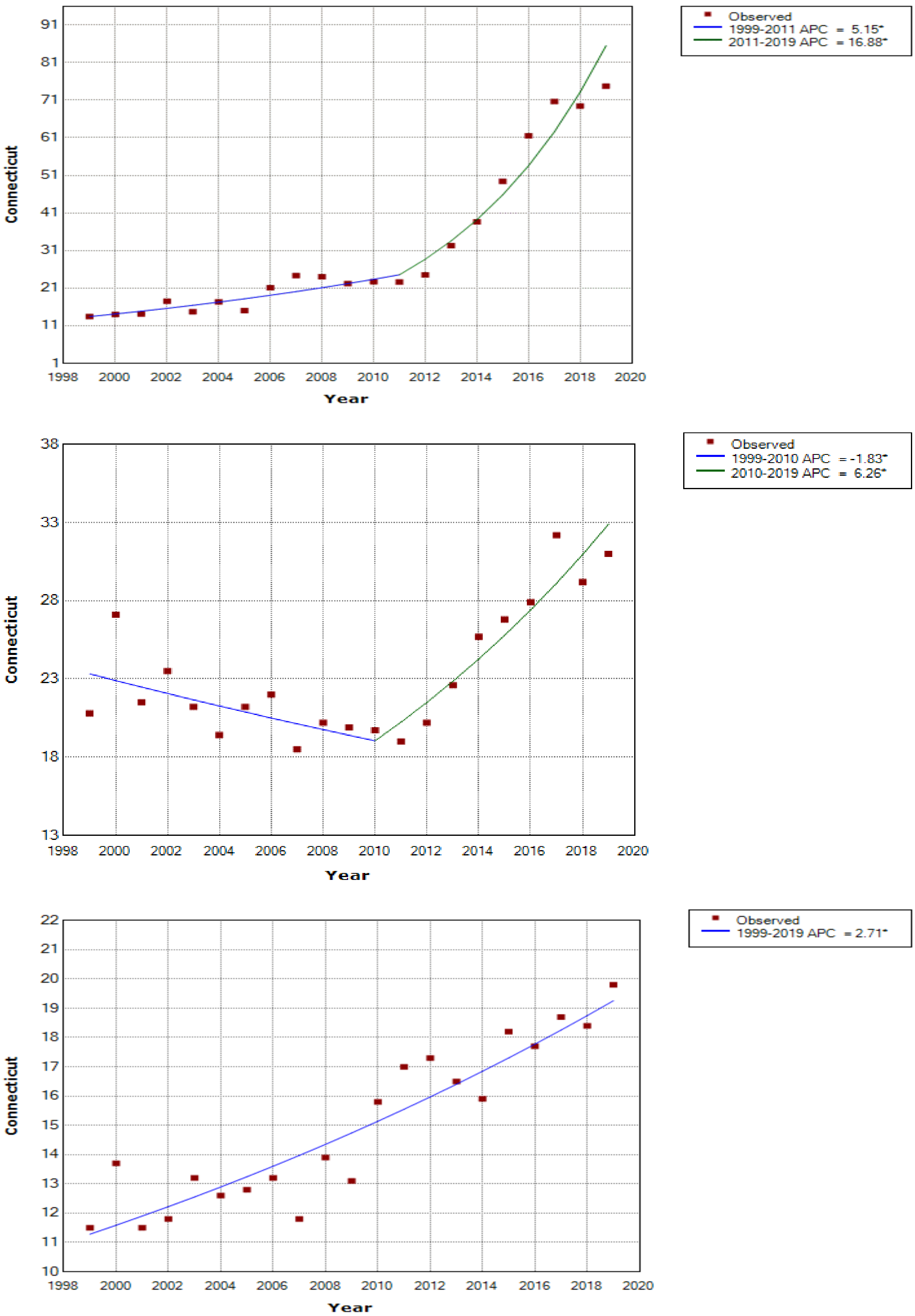
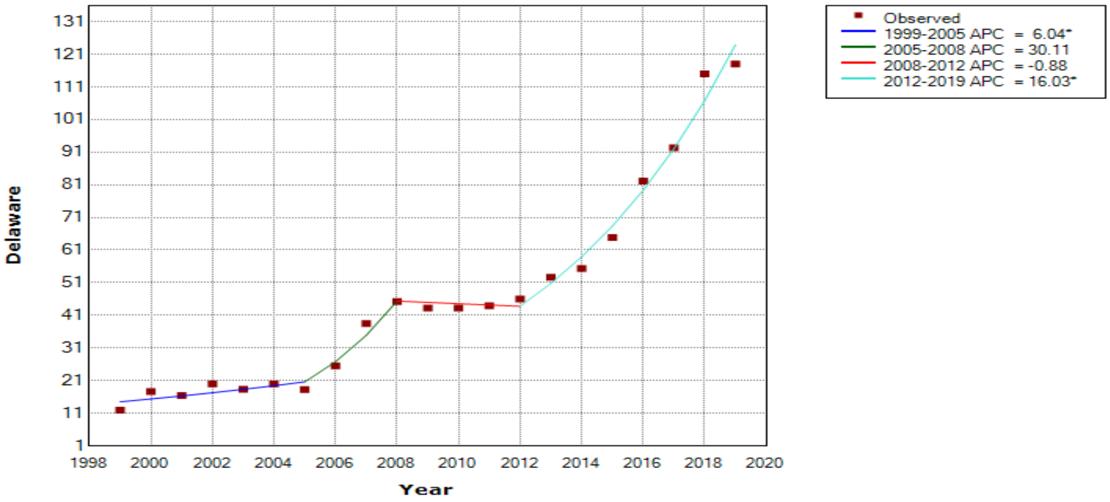
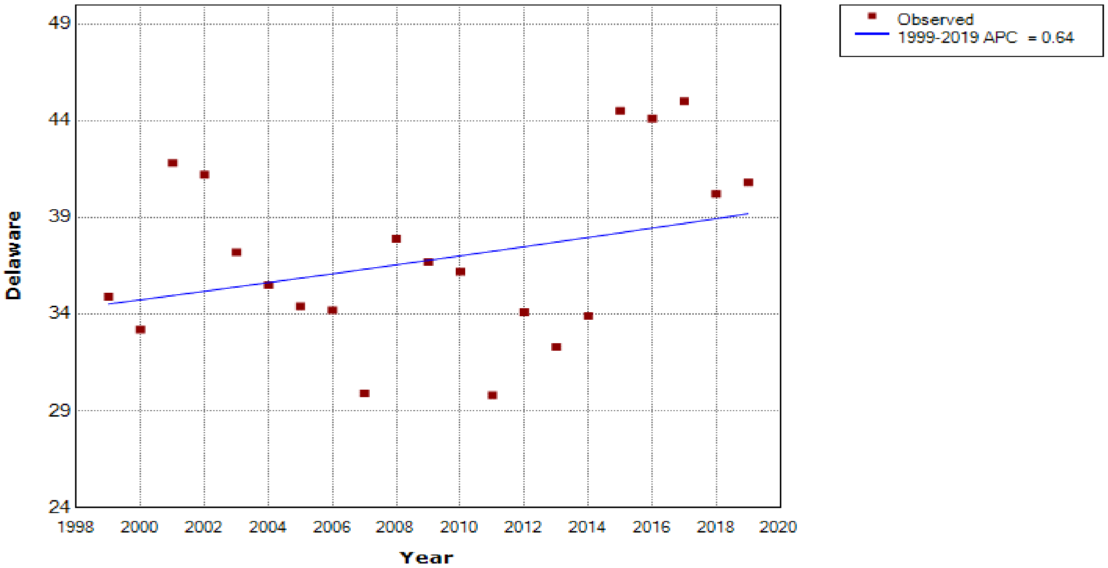


Figure 23. Trends of DoD in Delaware





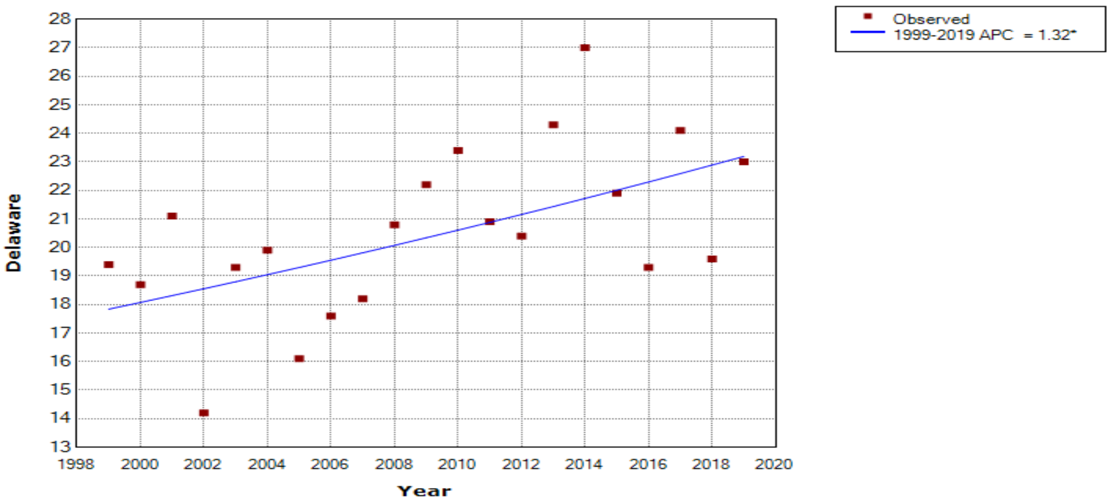


Figure 24. Trends of DoD in Florida

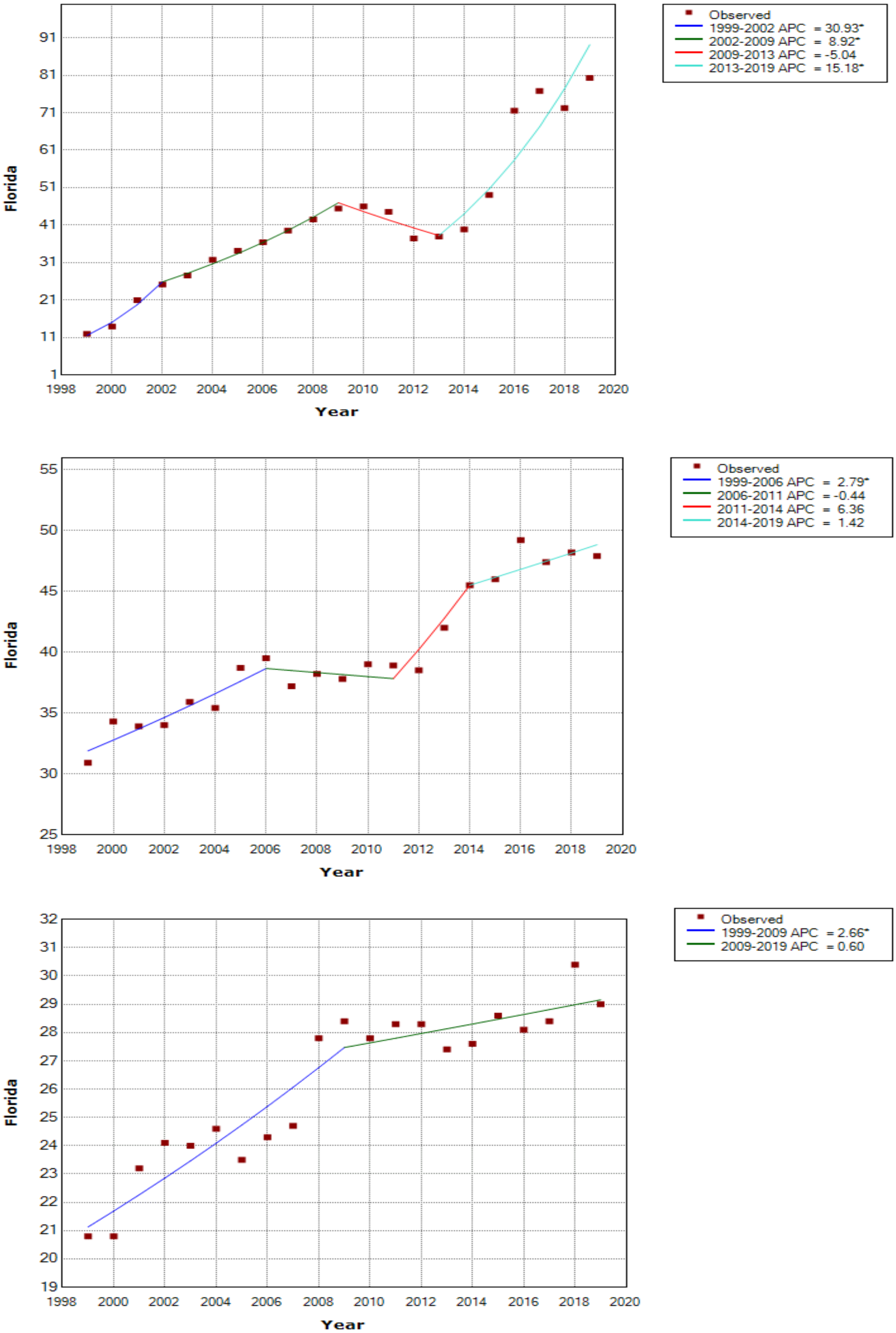
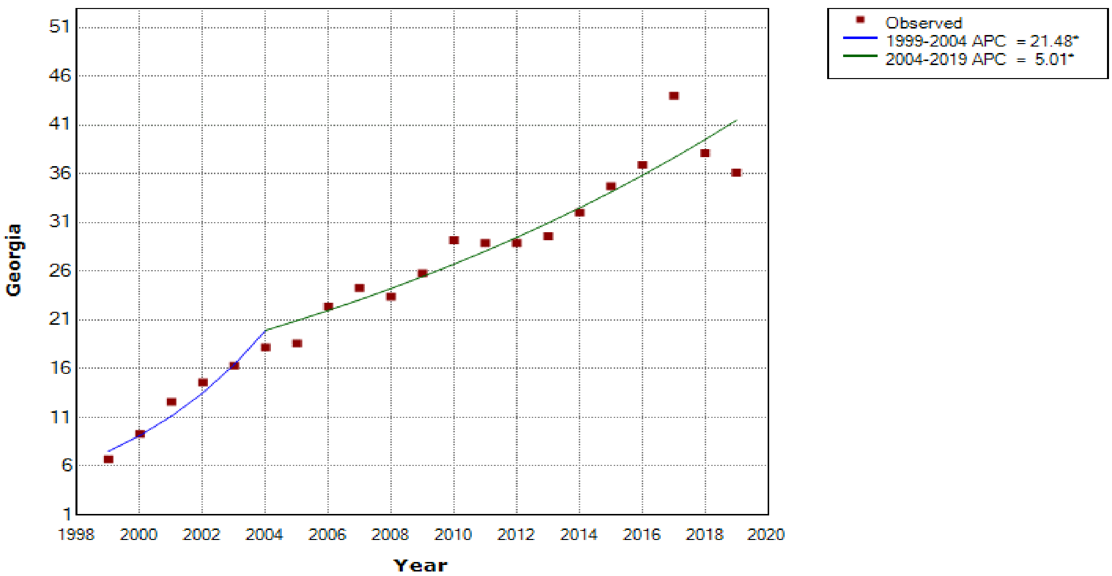
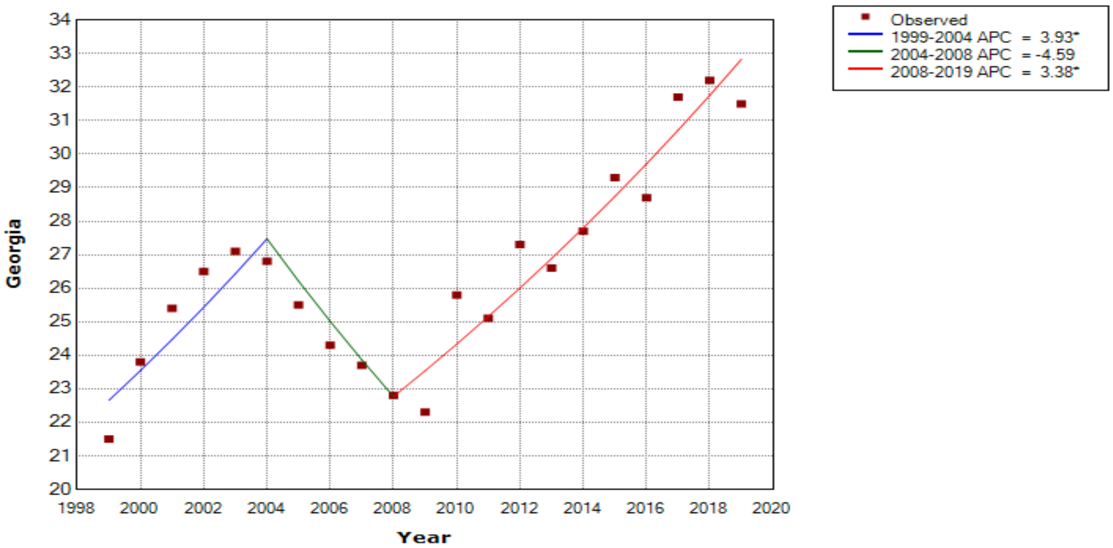


Figure 25. Trends of DoD in Georgia





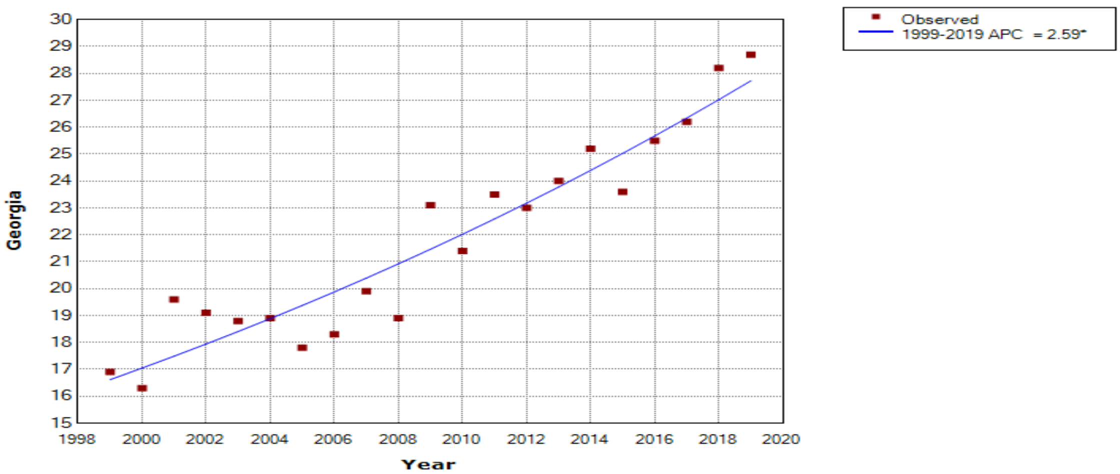
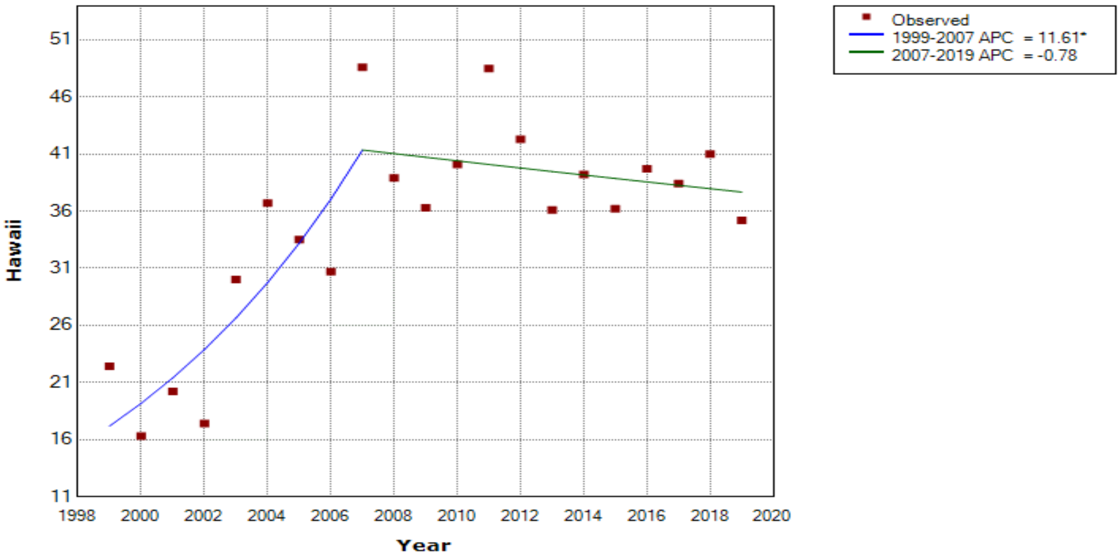
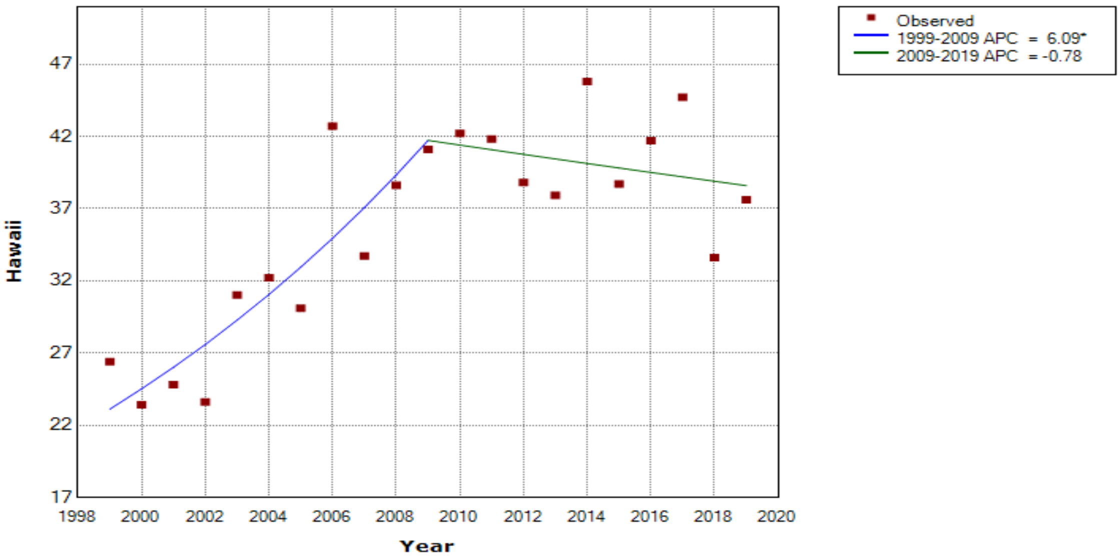


Figure 26. Trends of DoD in Hawaii





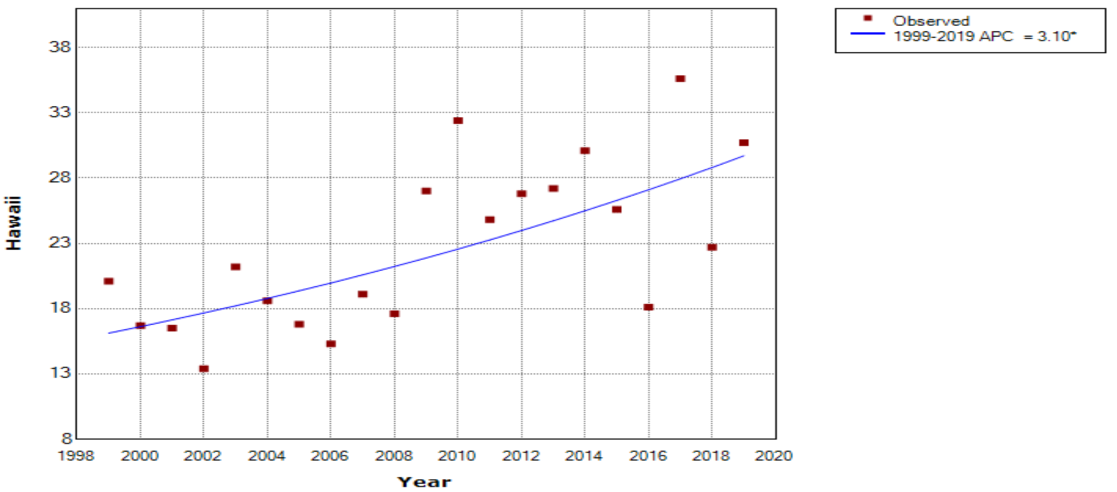
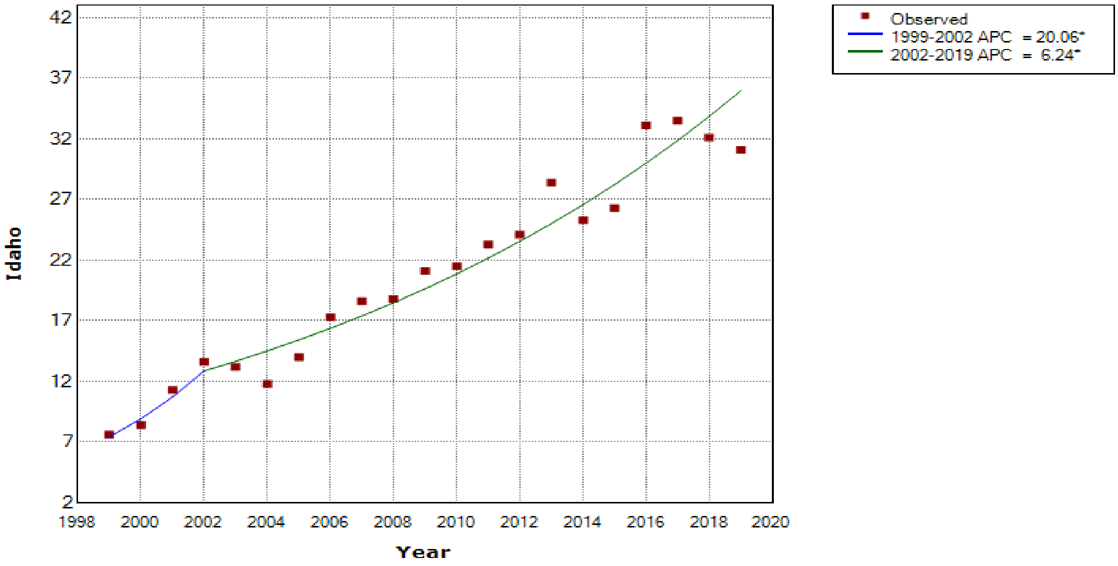
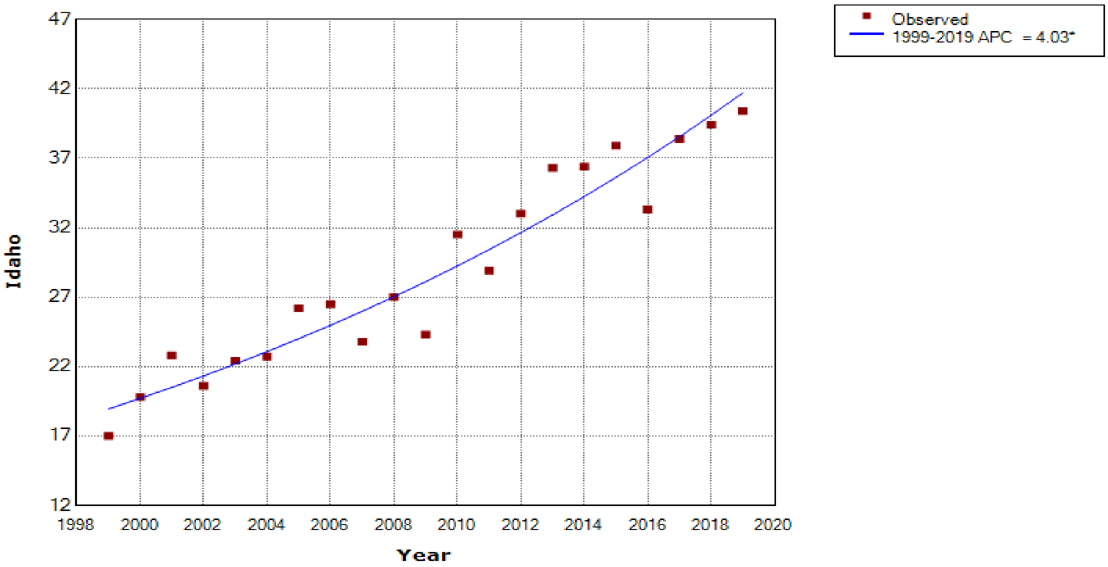


Figure 27. Trends of DoD in Idaho





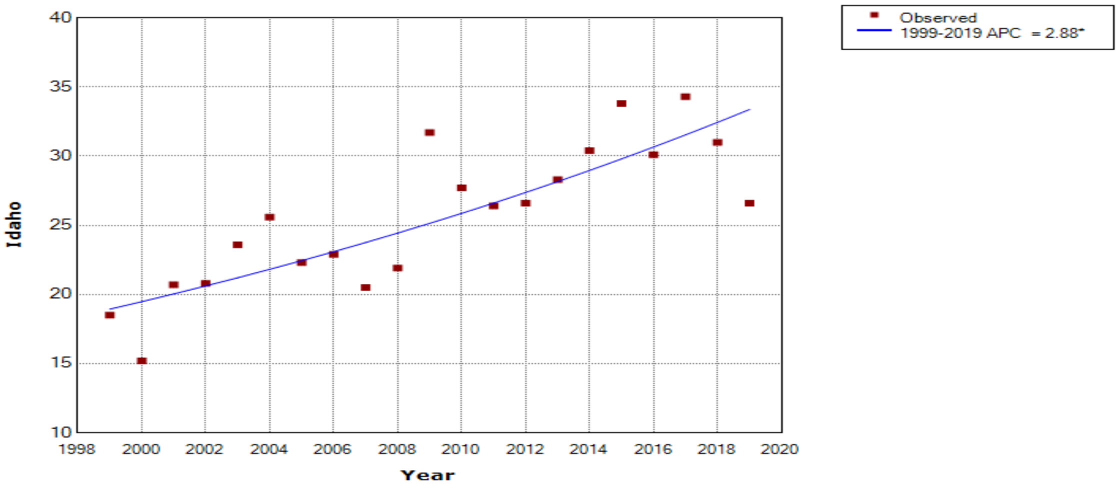


Figure 28. Trends of DoD in Illinois

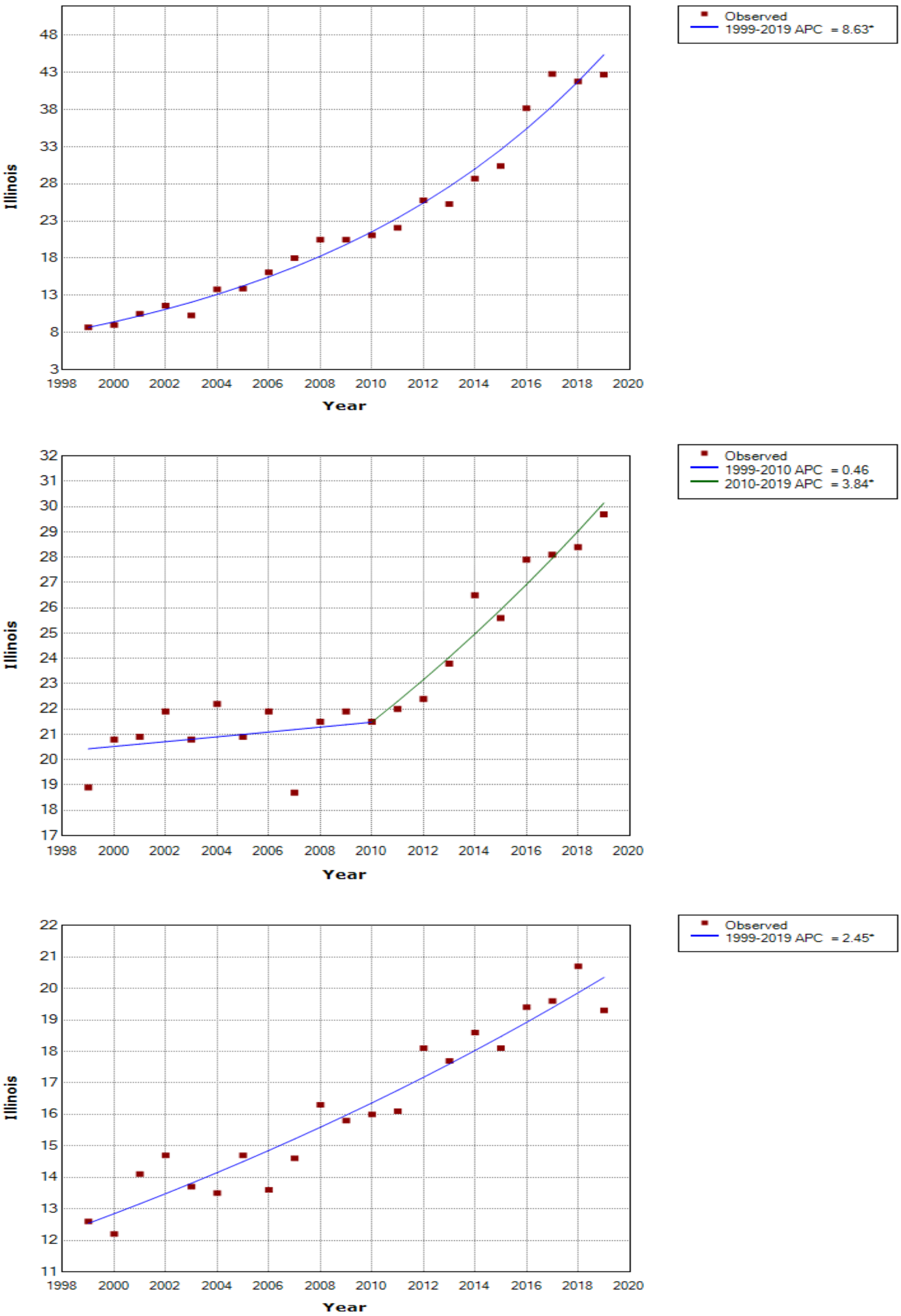
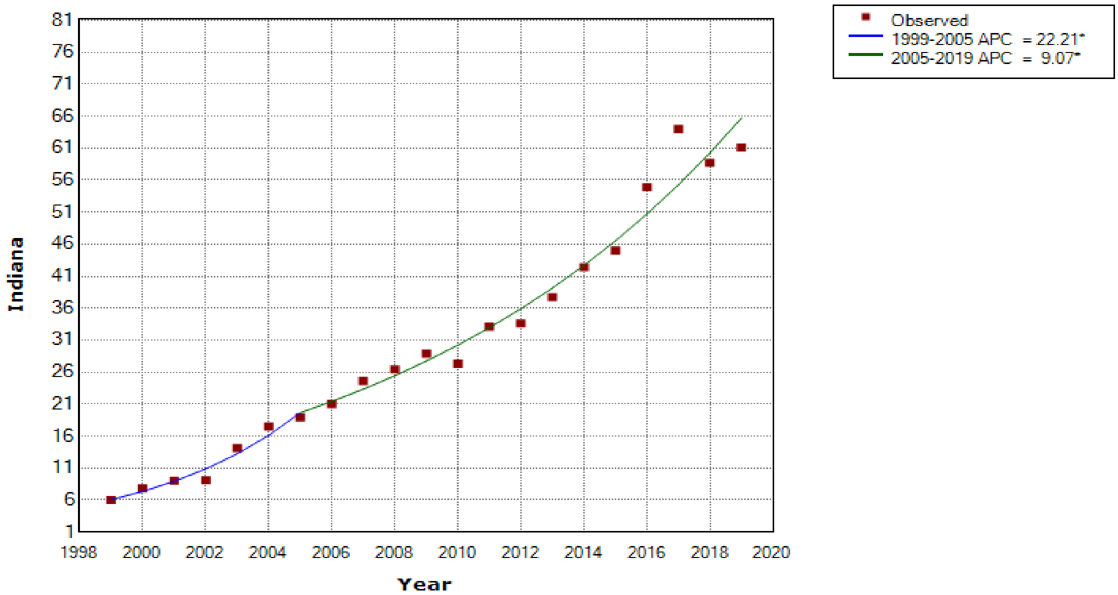
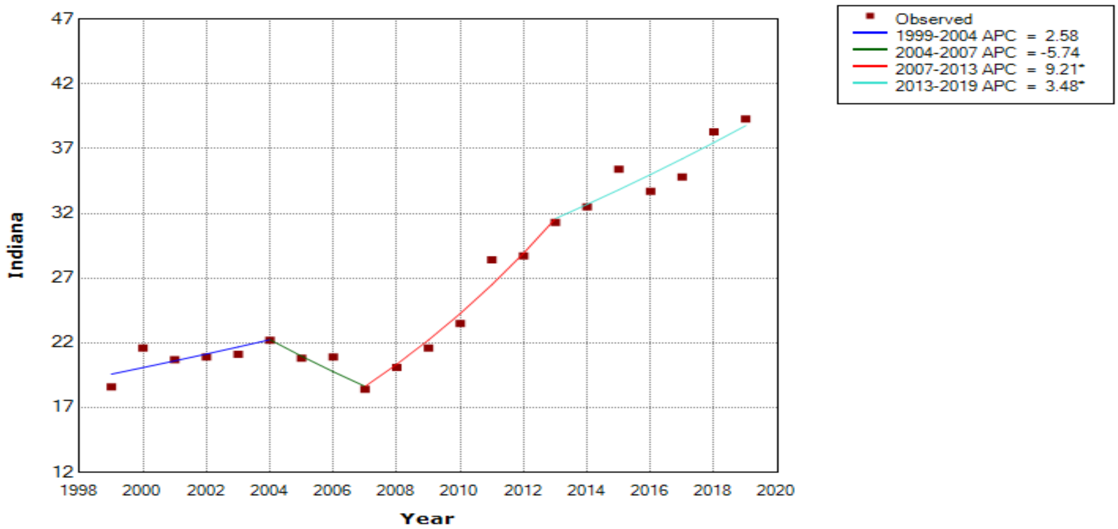


Figure 29. Trends of DoD in Indiana





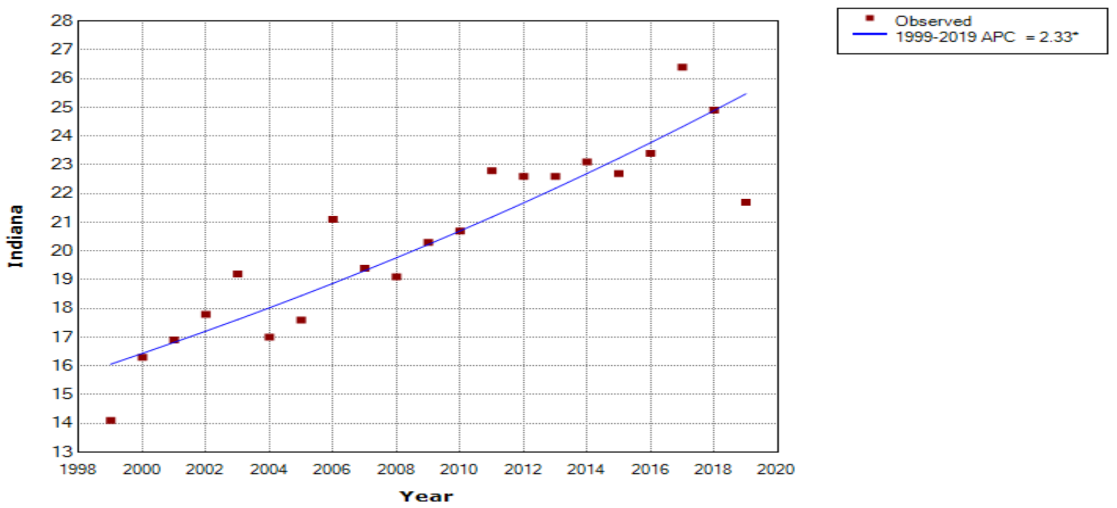
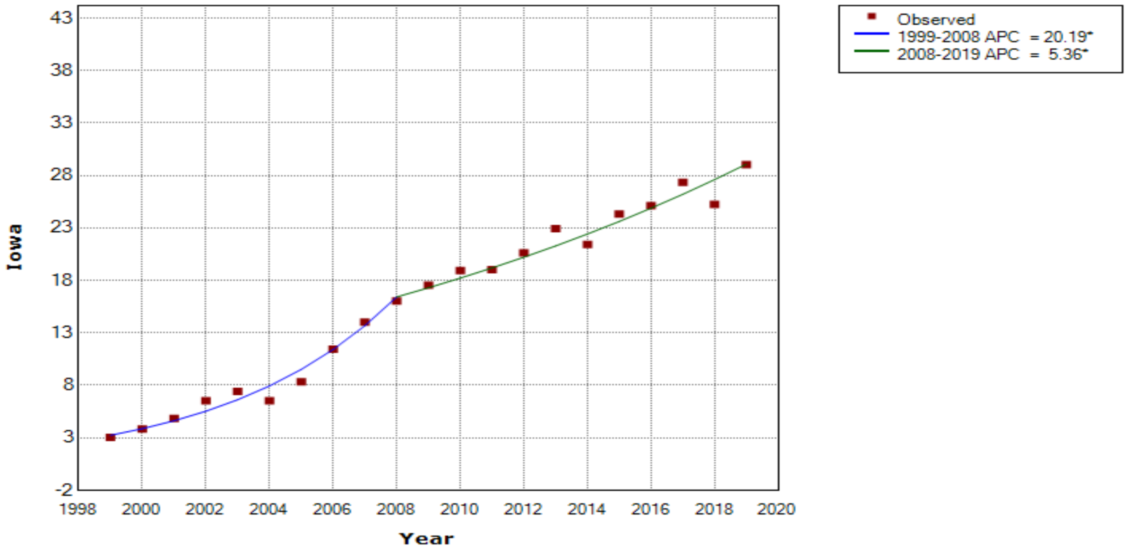
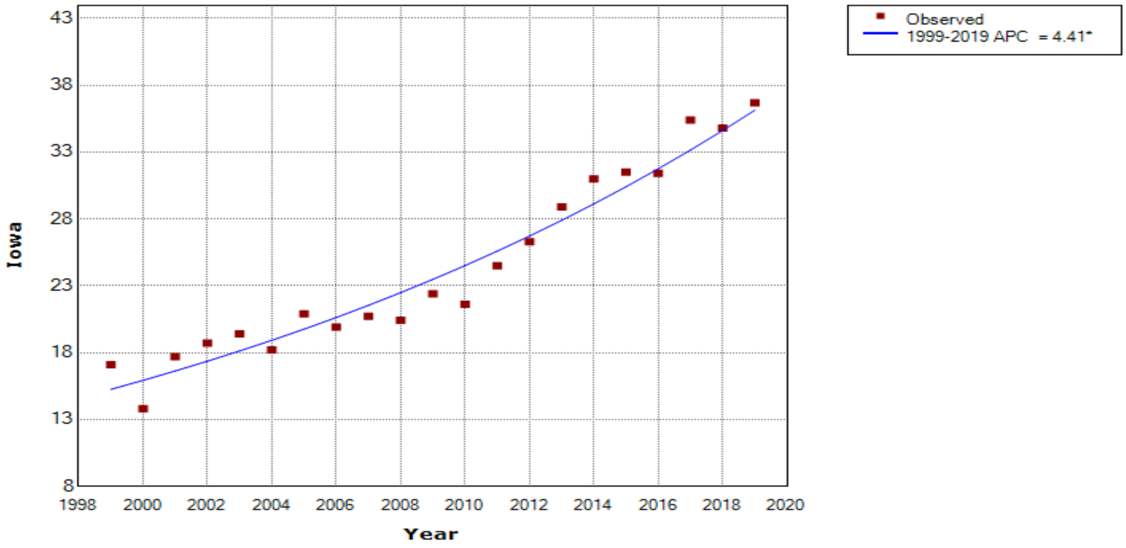


Figure 30. Trends of DoD in Iowa





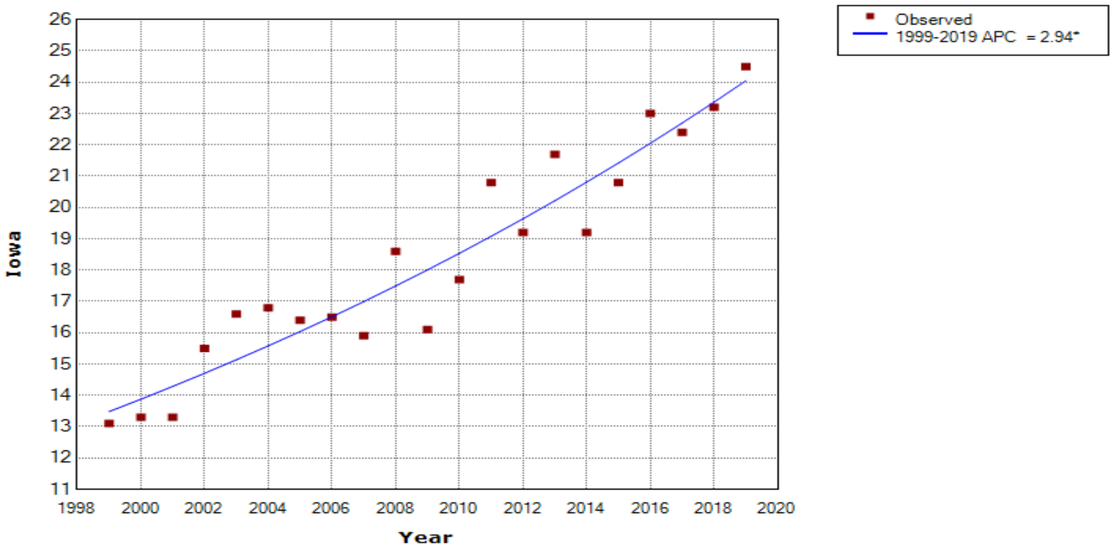
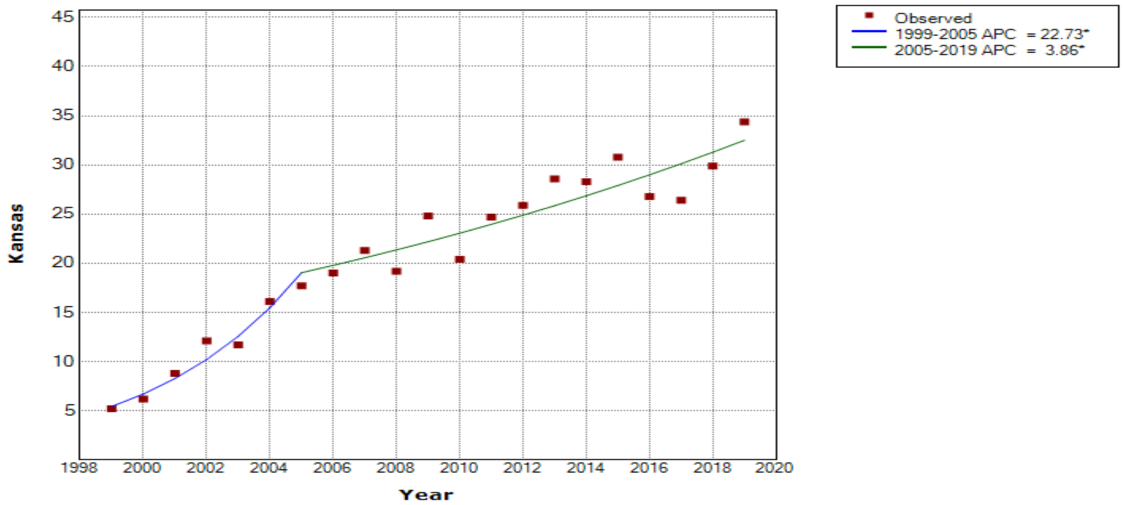
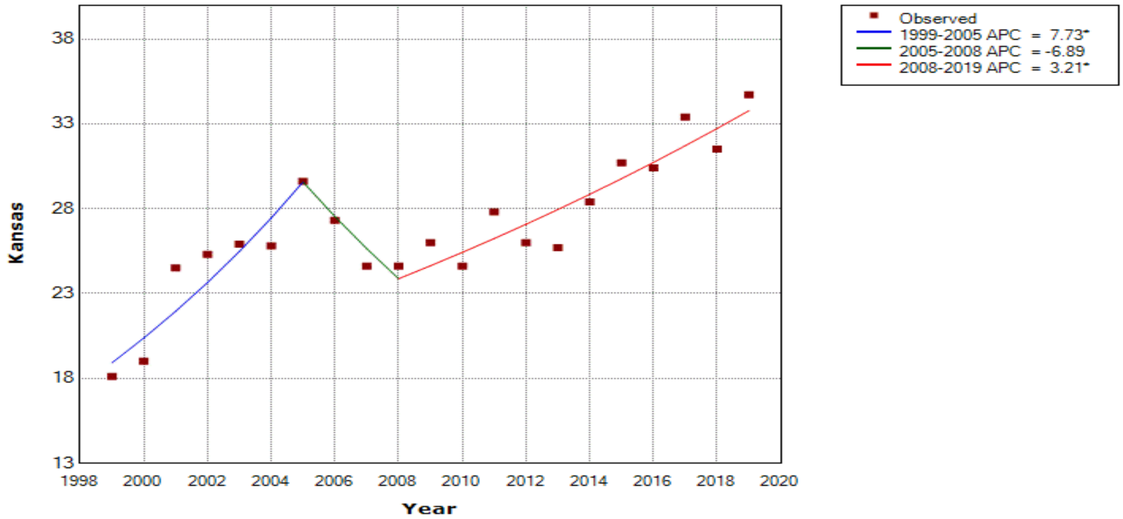


Figure 31. Trends of DoD in Kansas





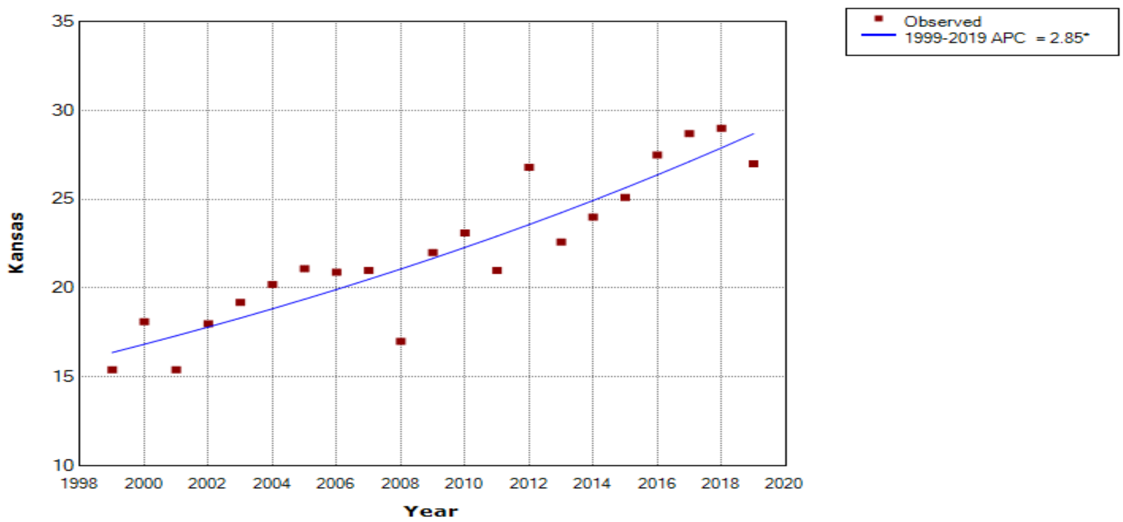
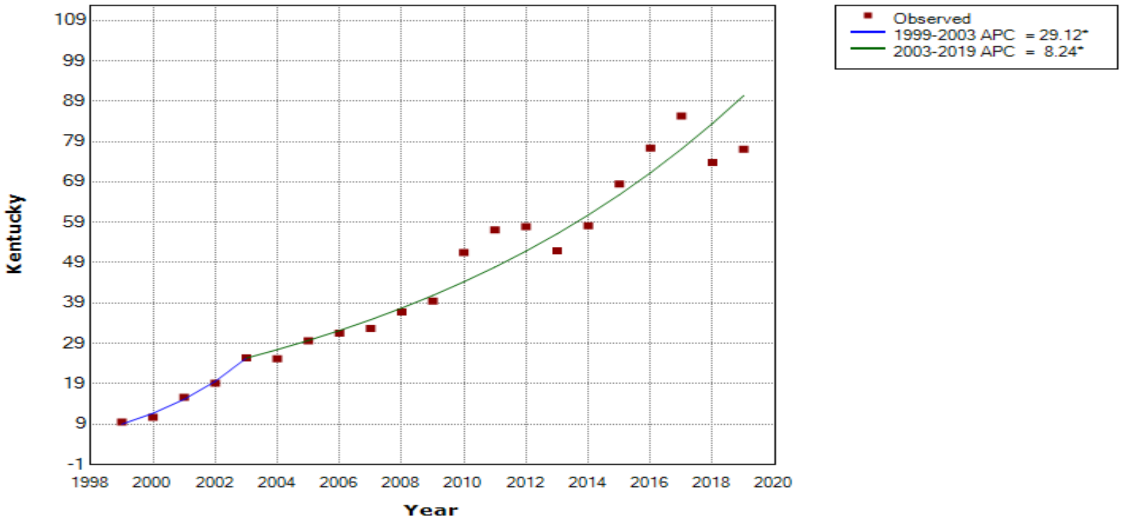
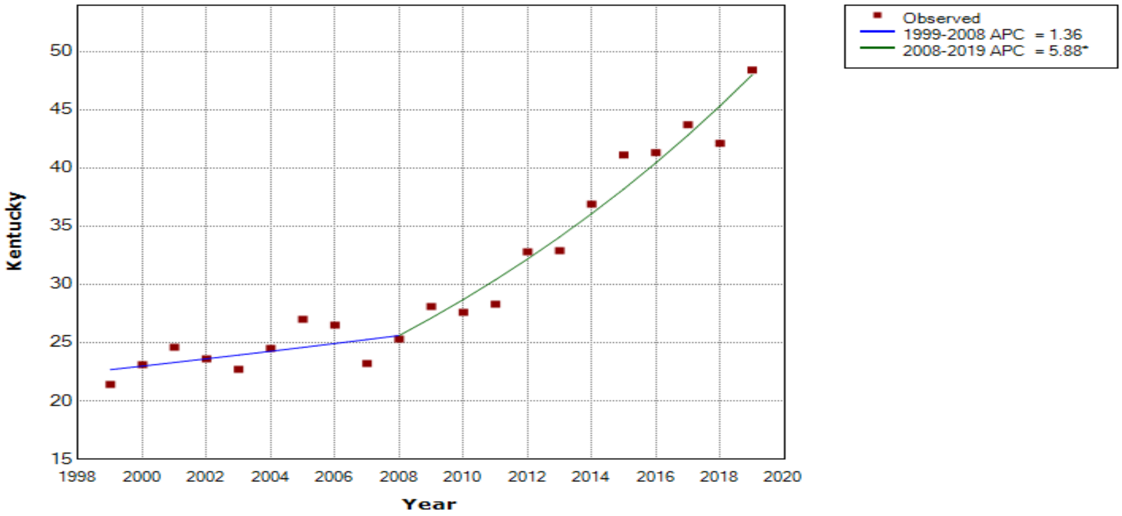


Figure 32. Trends of DoD in Kentucky





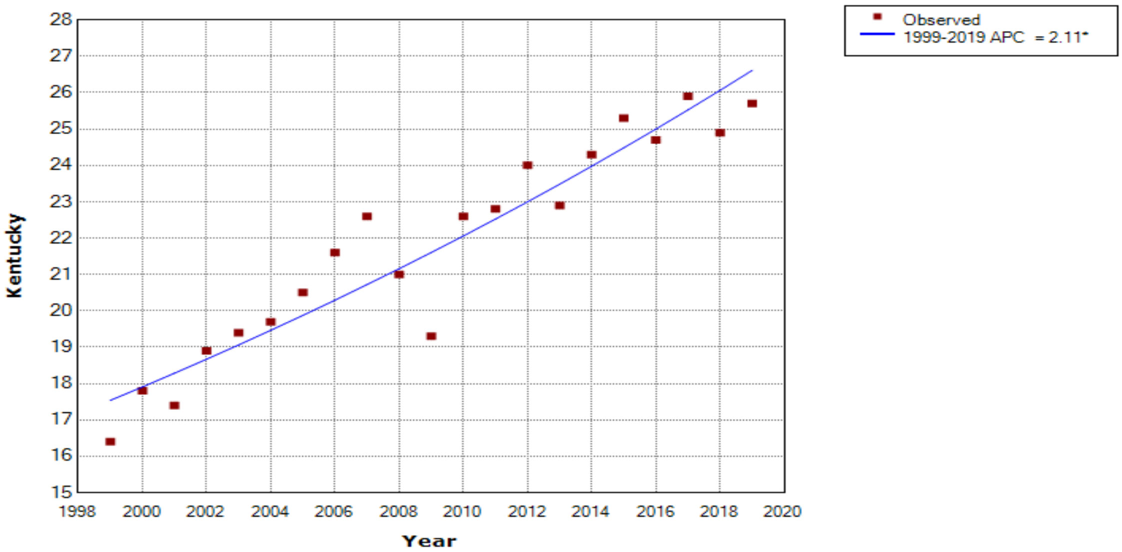


Figure 33. Trends of DoD in Louisiana

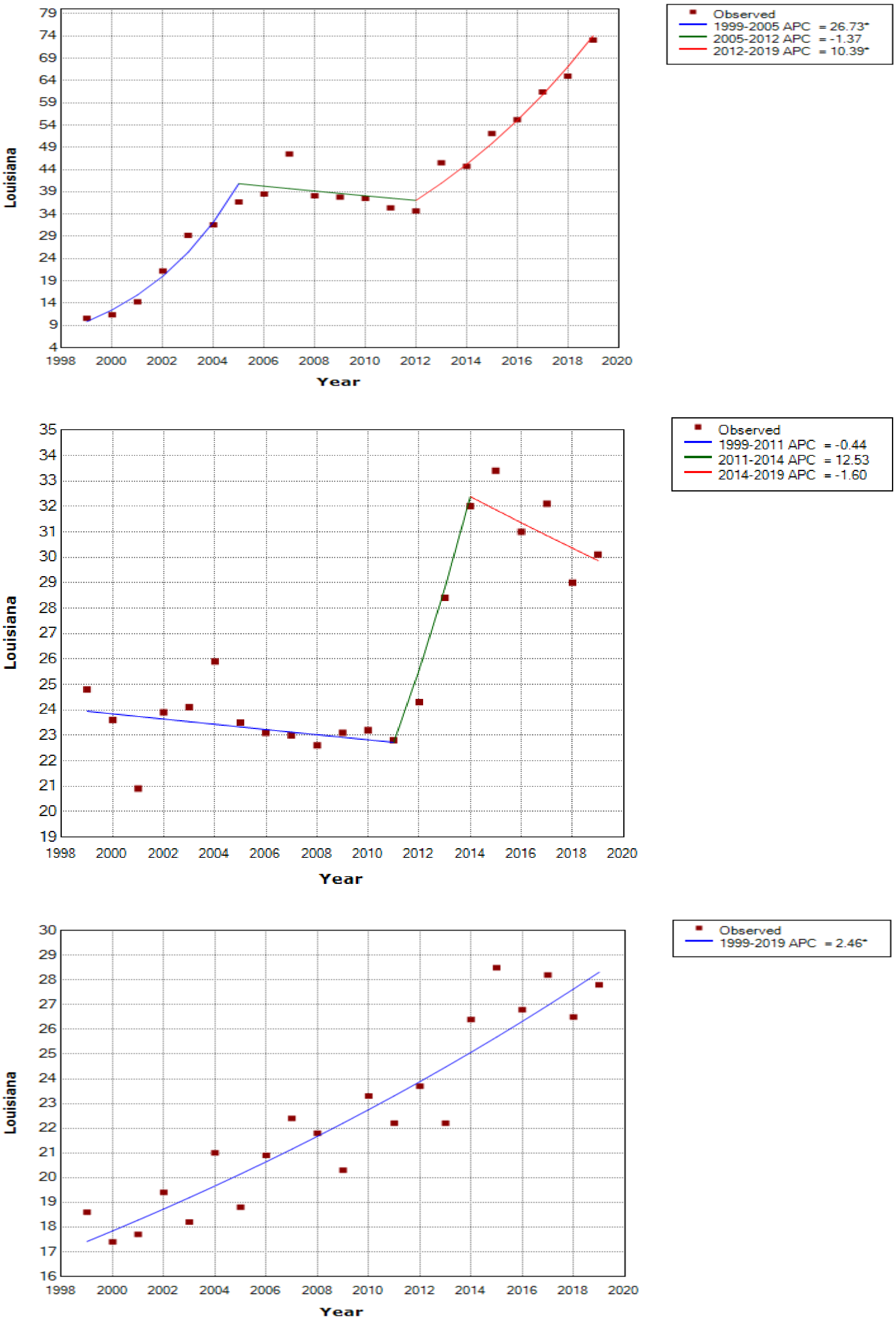
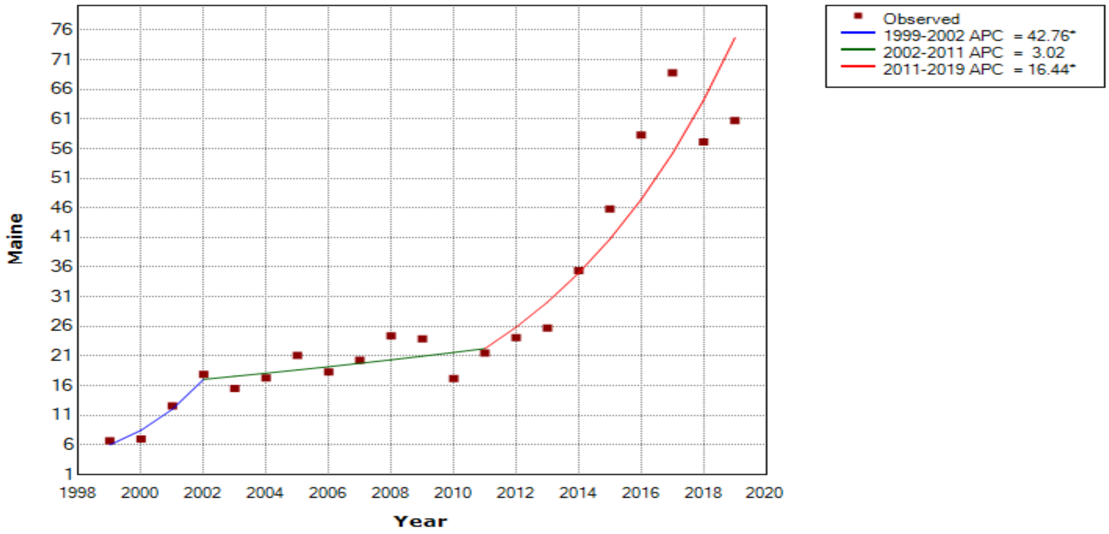
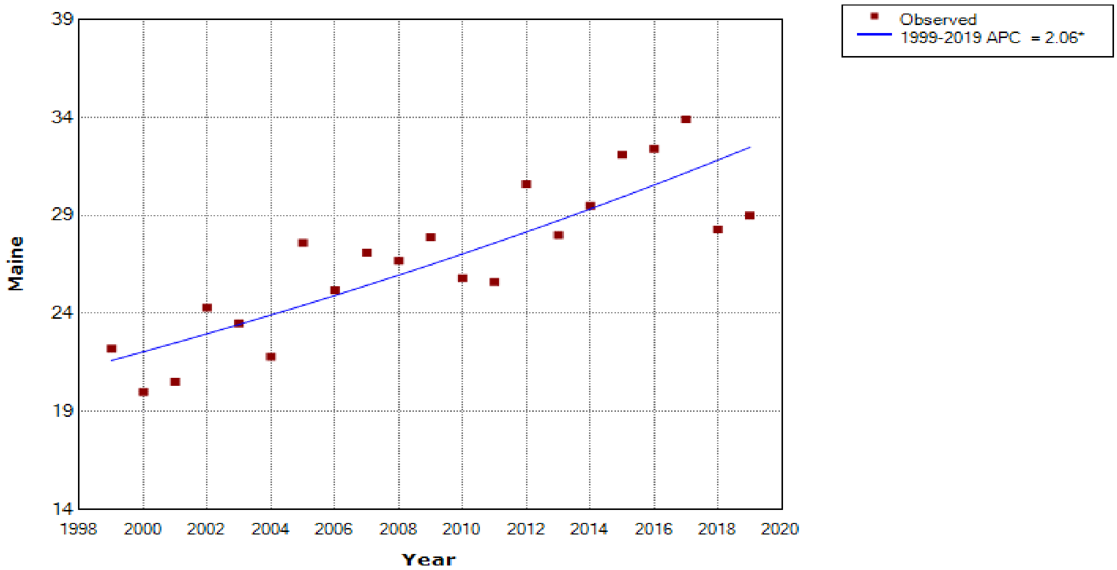


Figure 34. Trends of DoD in Maine





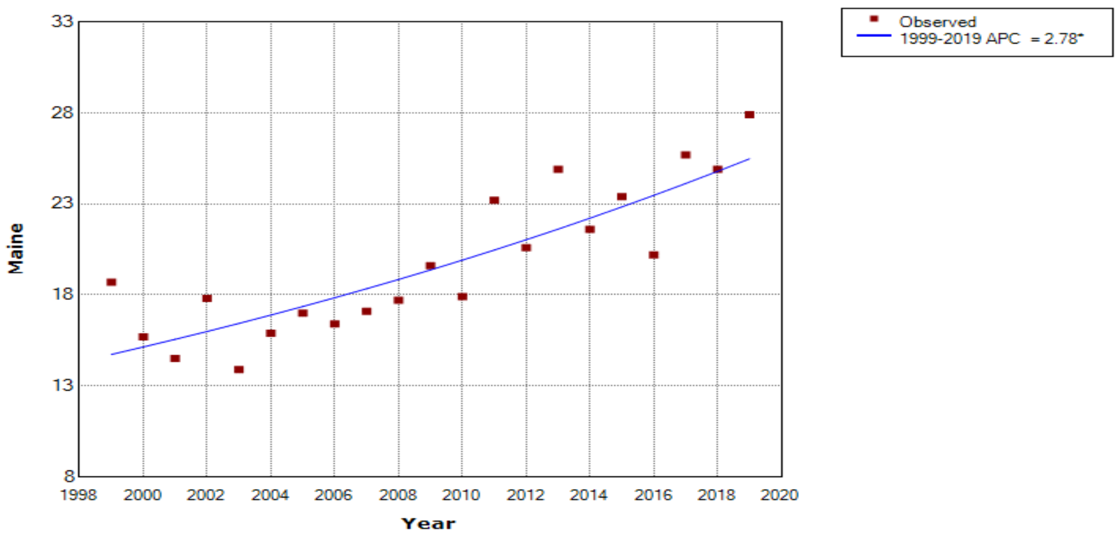
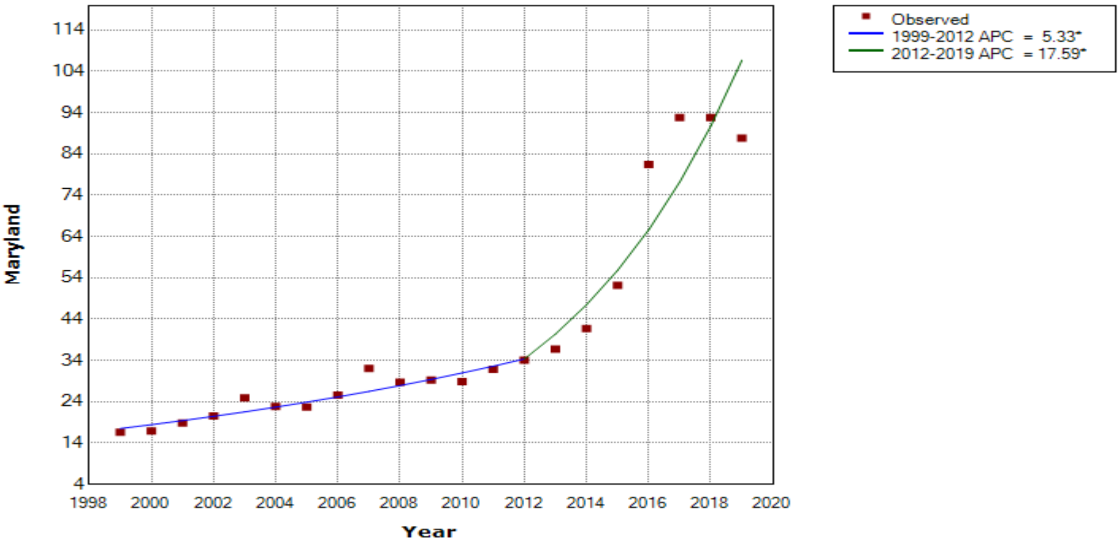
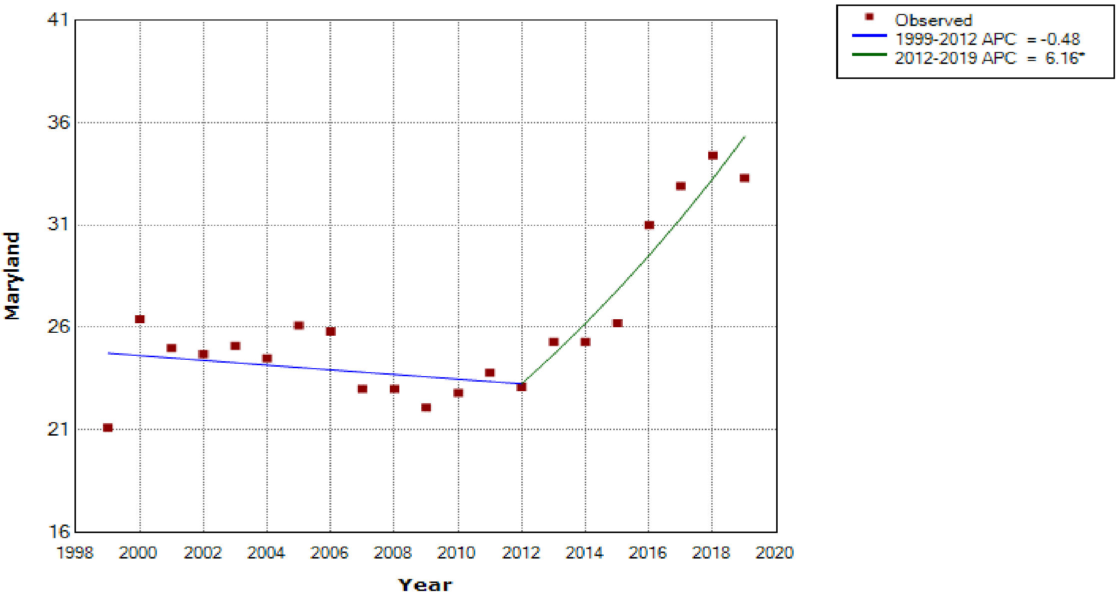


Figure 35. Trends of DoD in Maryland





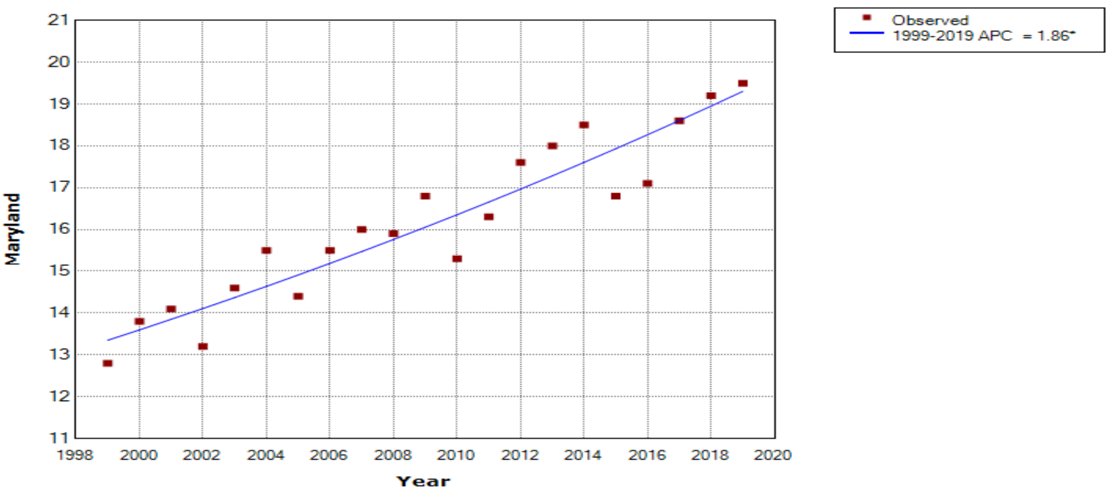
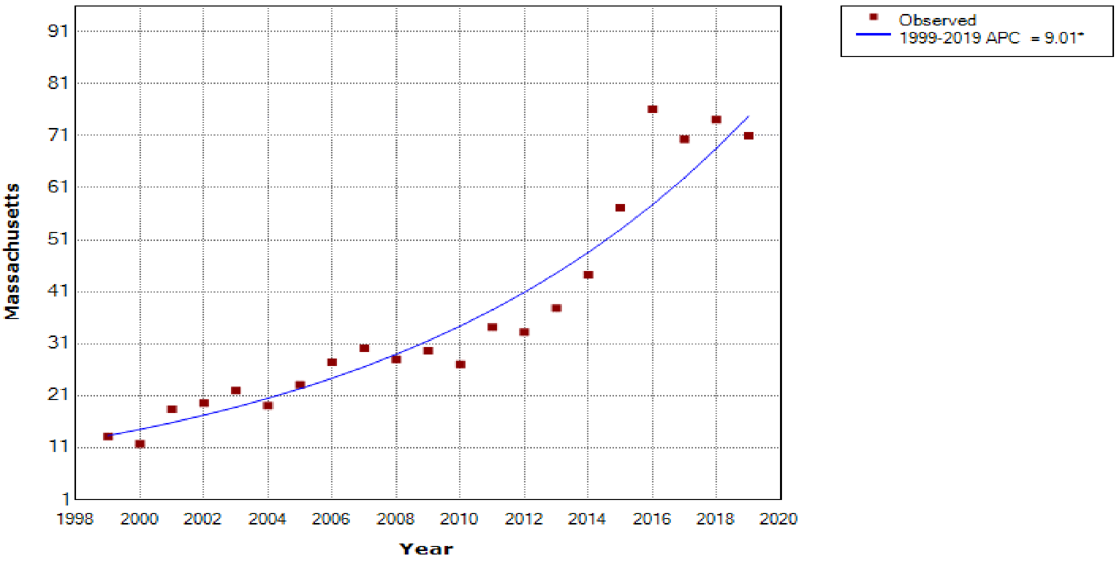
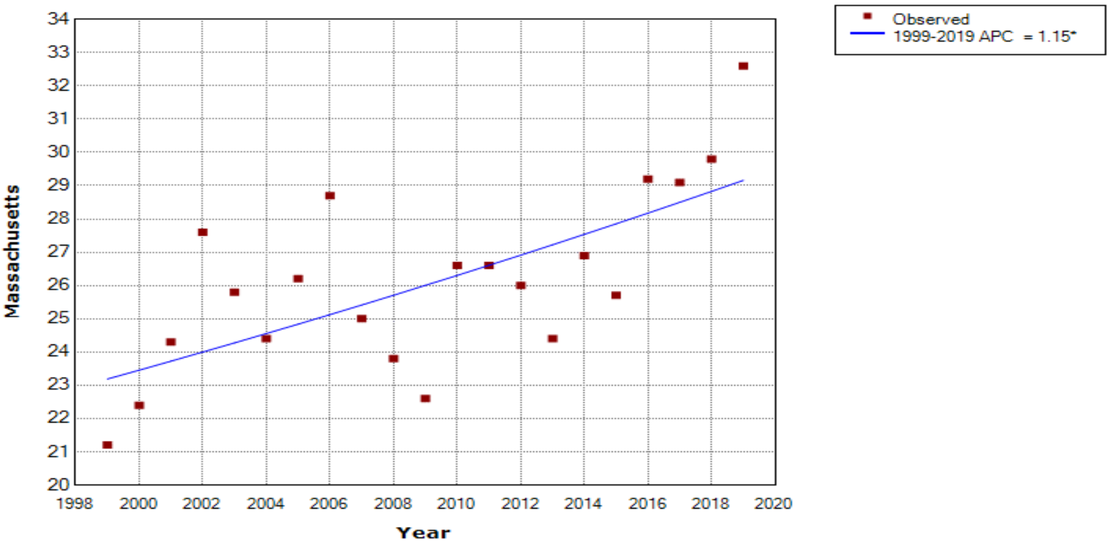


Figure 36. Trends of DoD in Massachusetts





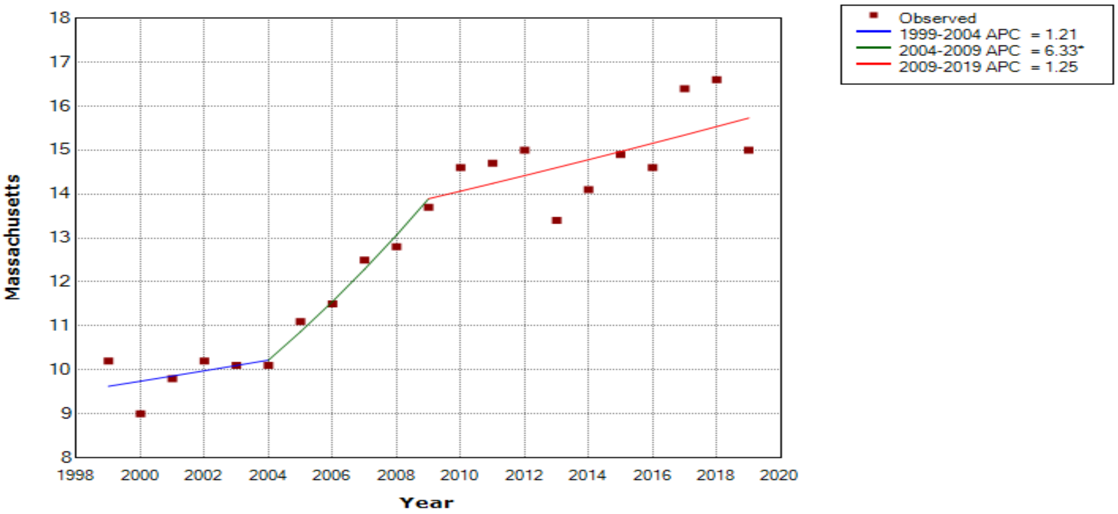


Figure 37. Trends of DoD in Michigan

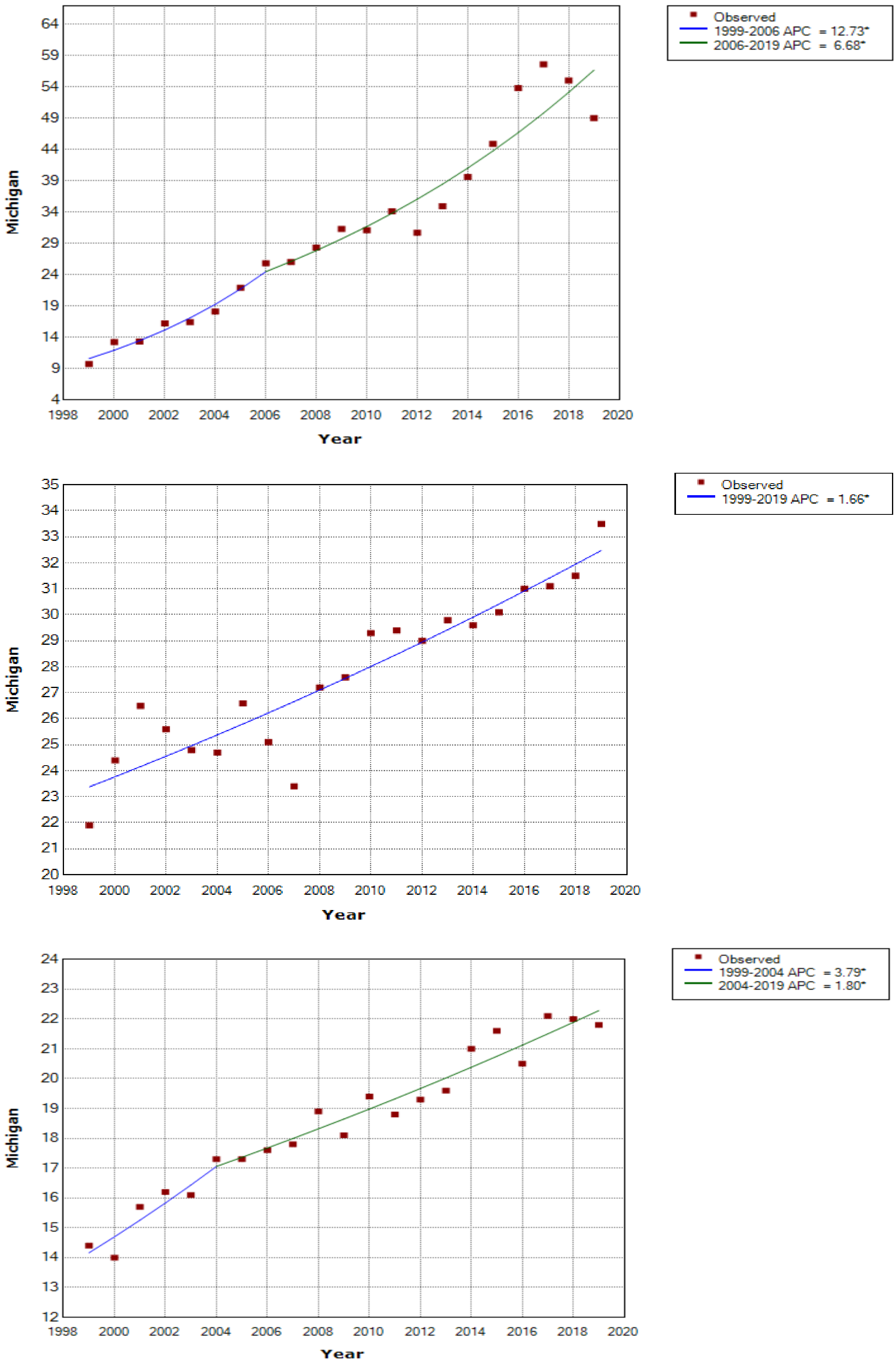


Figure 38. Trends of DoD in Minnesota

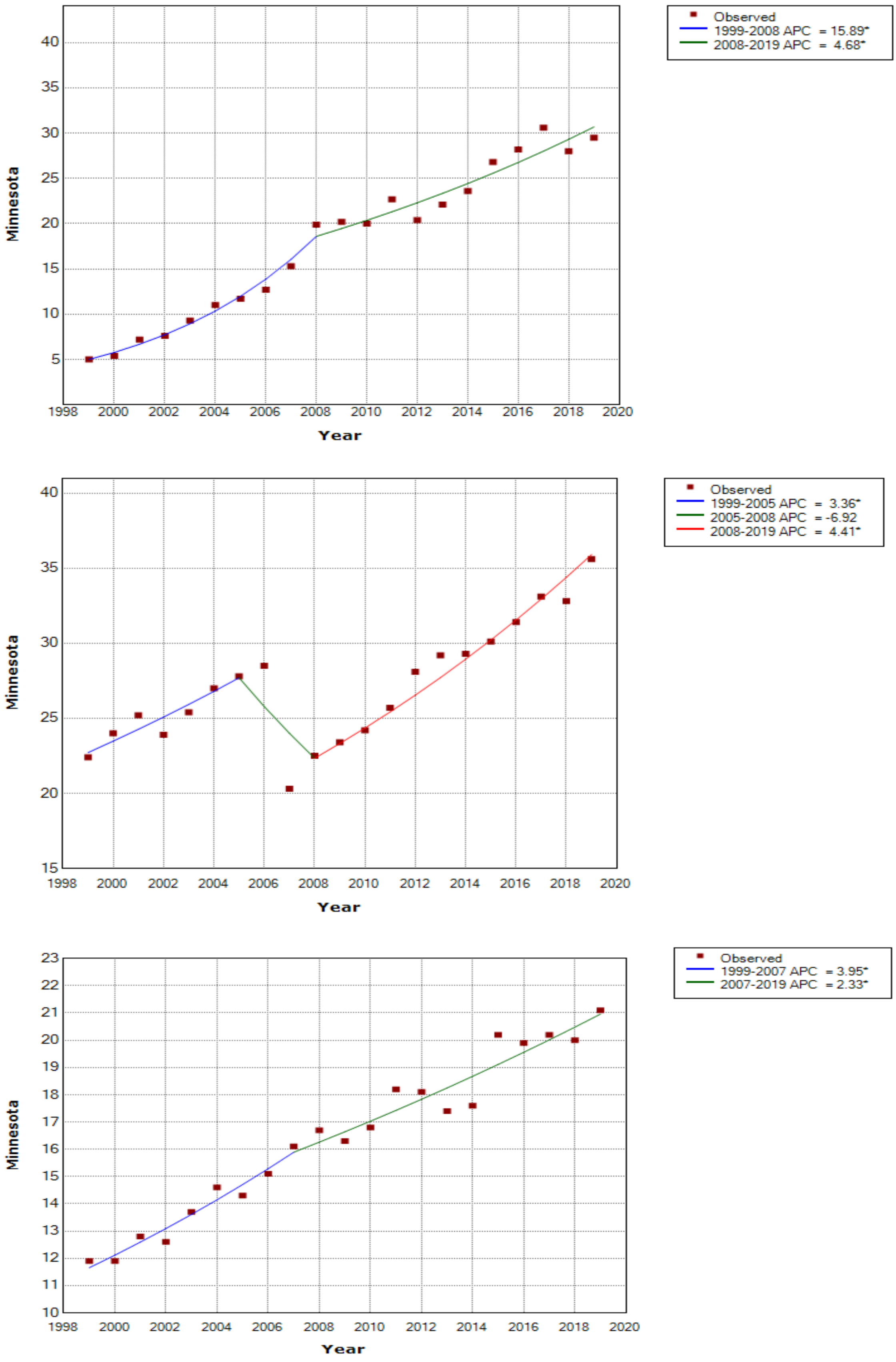
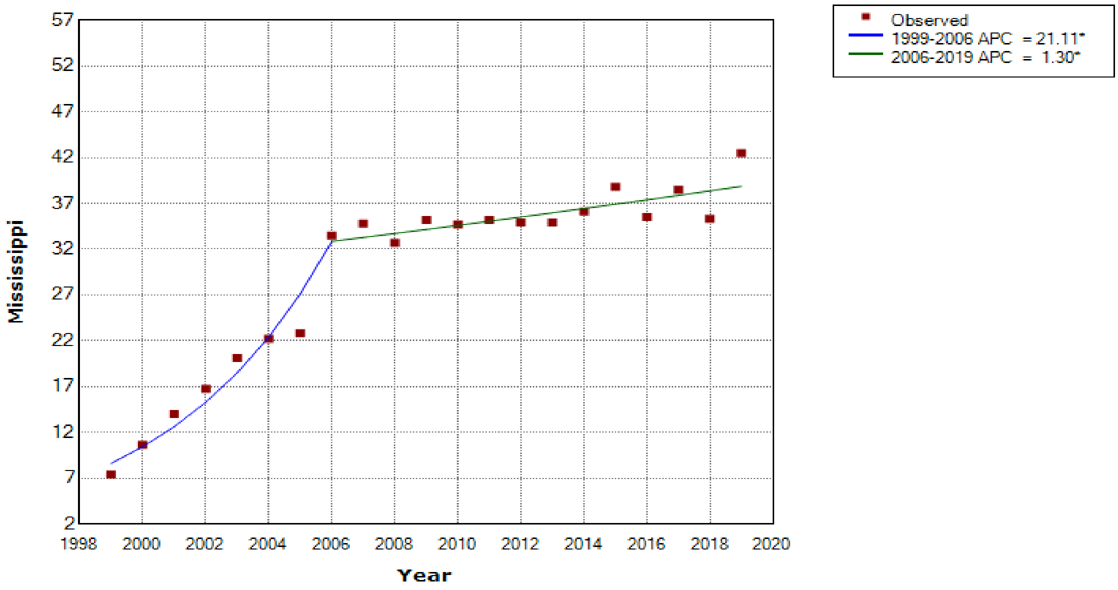
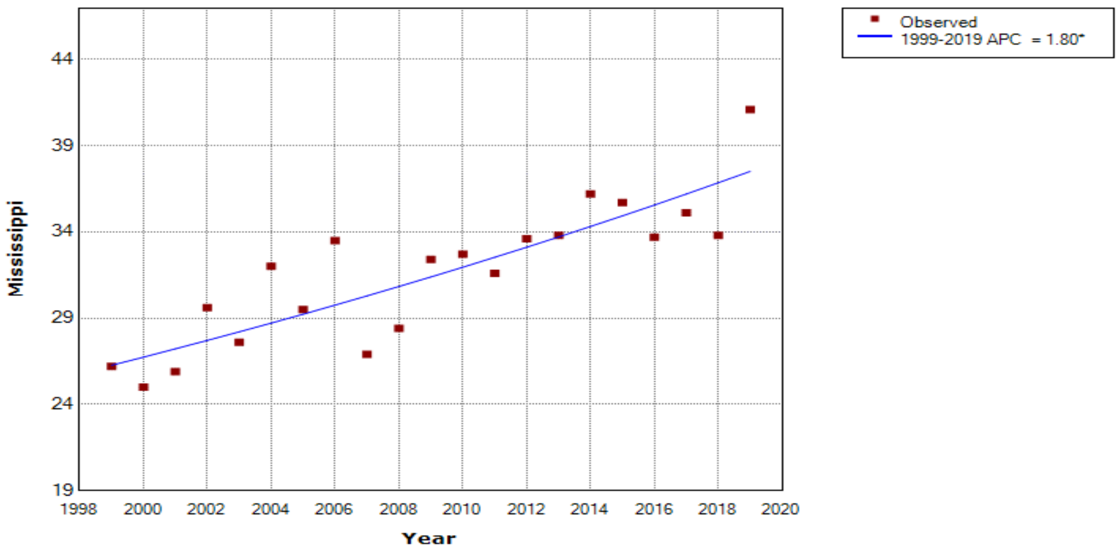


Figure 39. Trends of DoD in Mississippi





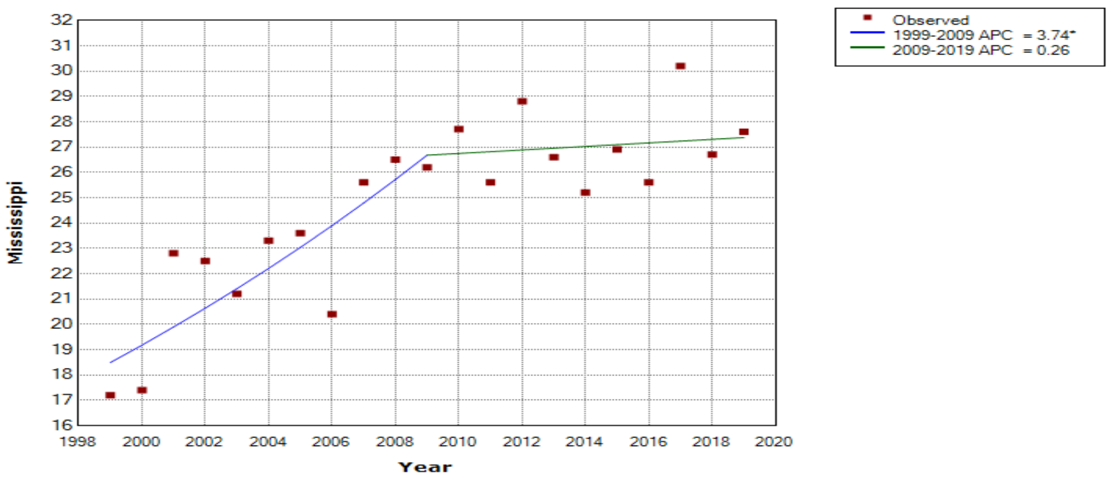
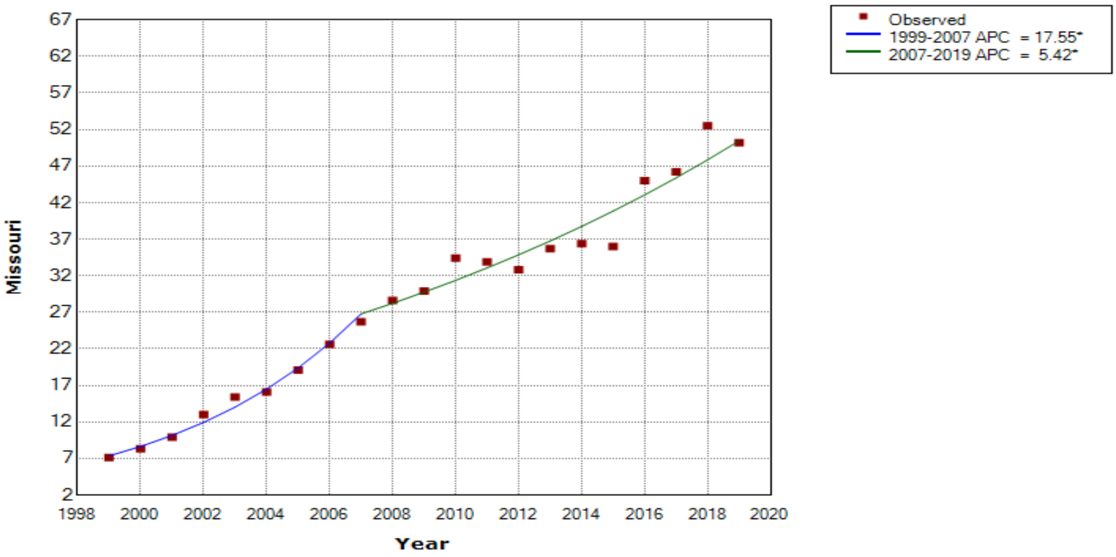
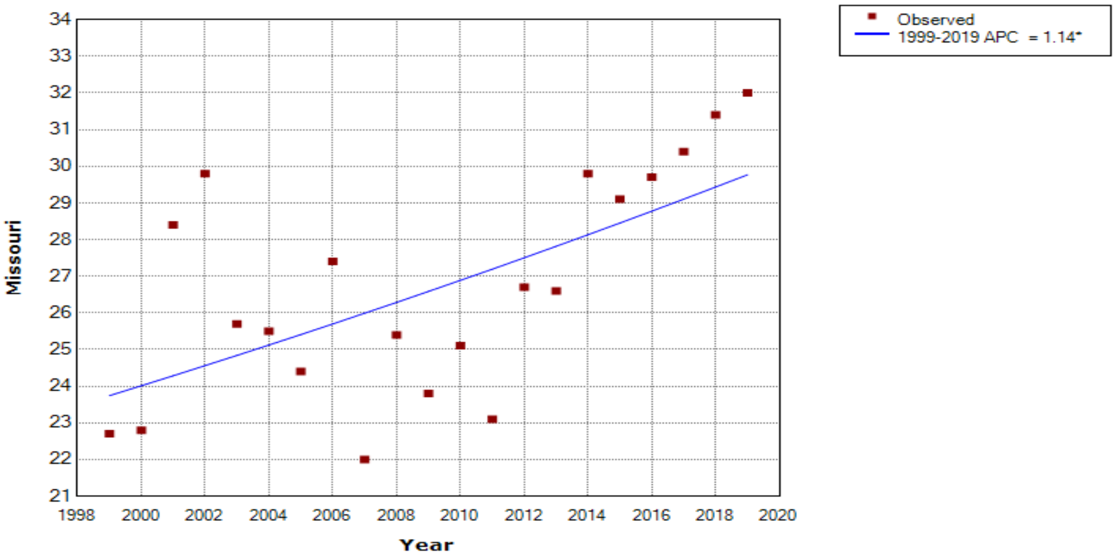


Figure 40. Trends of DoD in Missouri





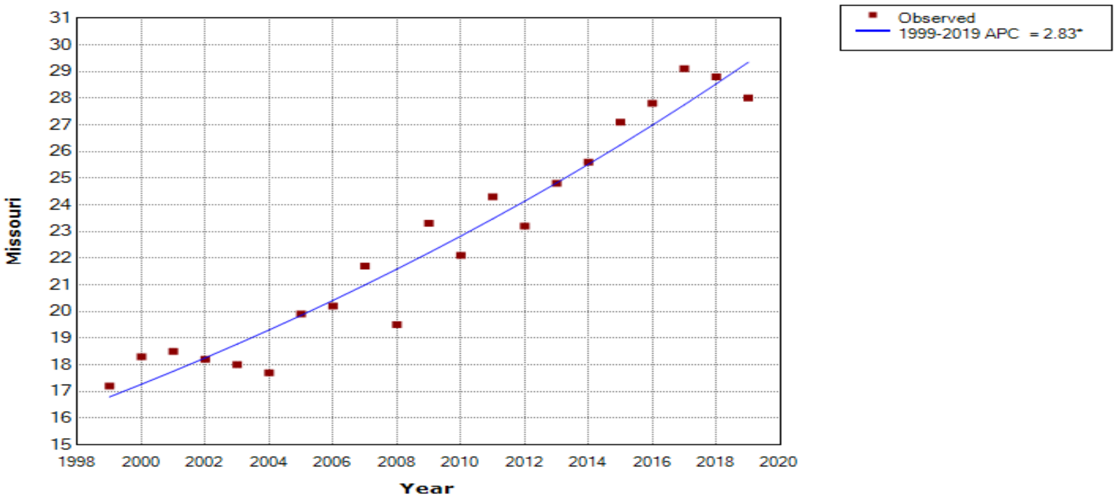


Figure 41. Trends of DoD in Montana

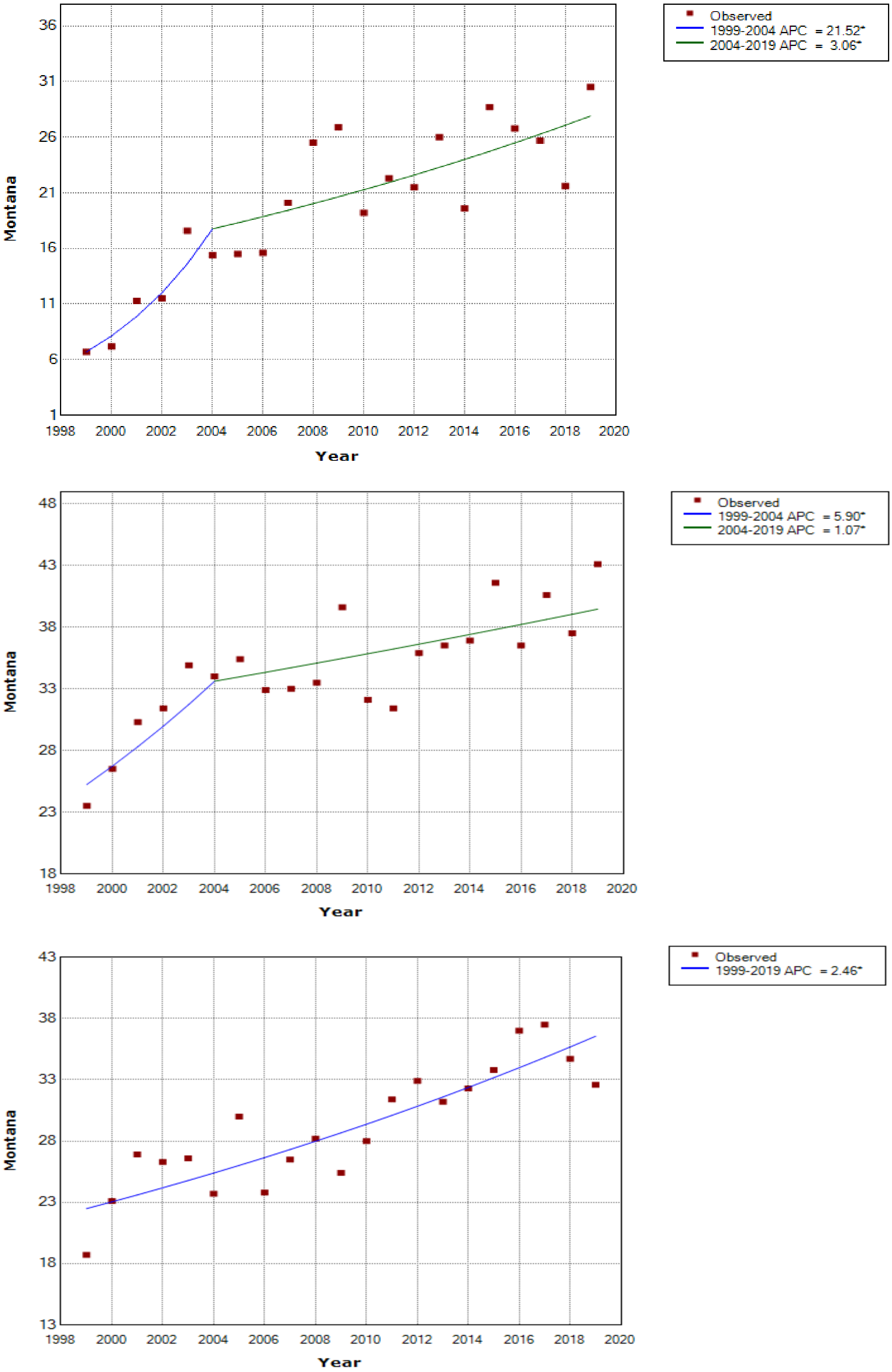
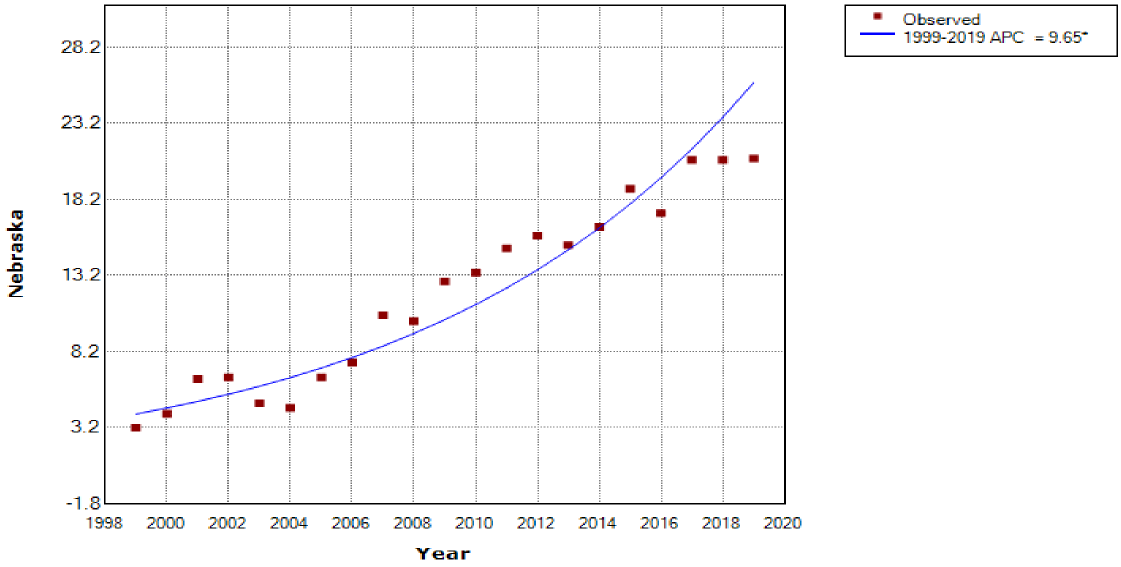
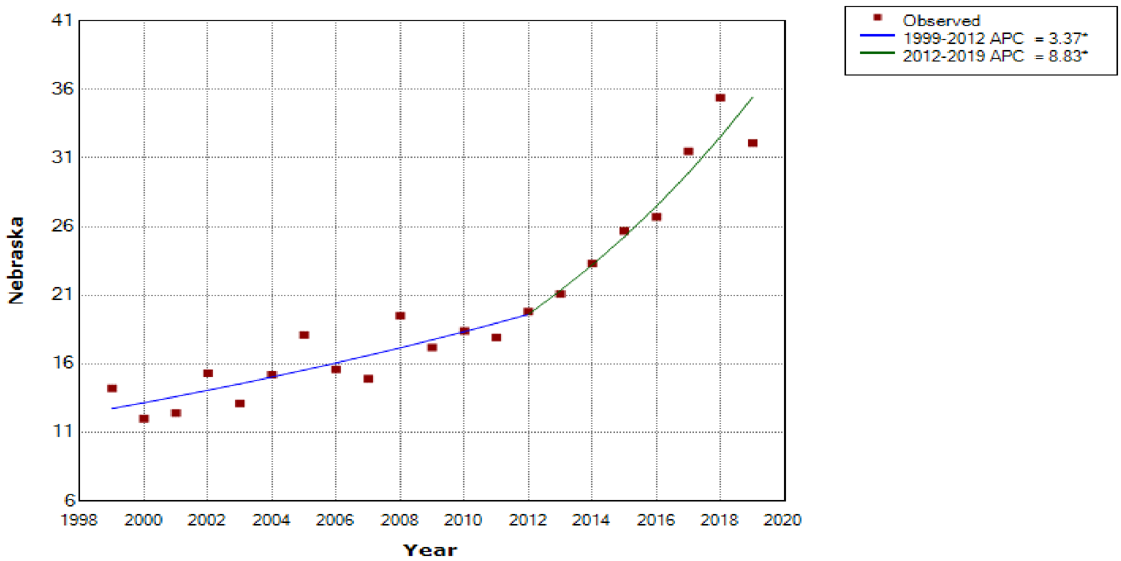


Figure 42. Trends of DoD in Nebraska





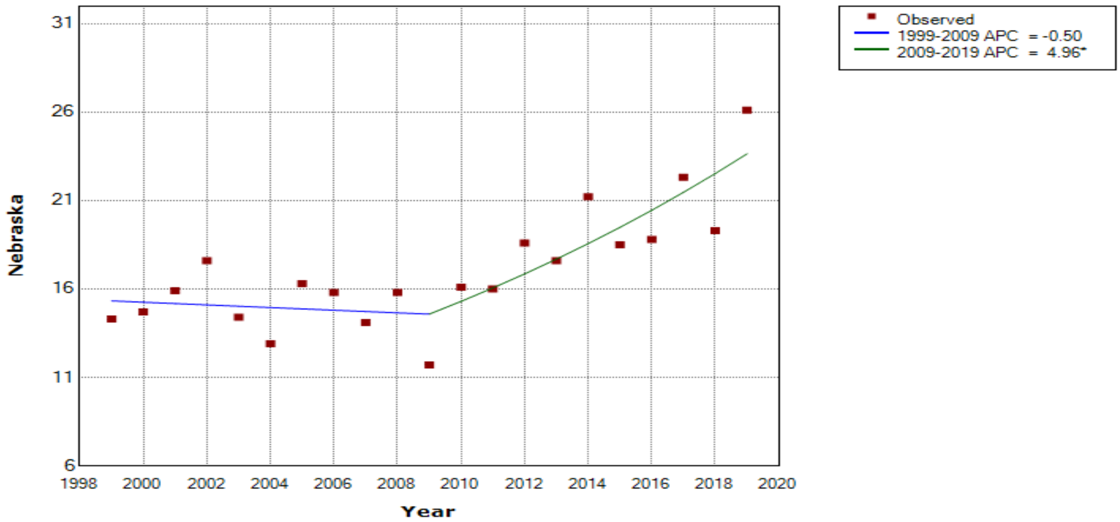
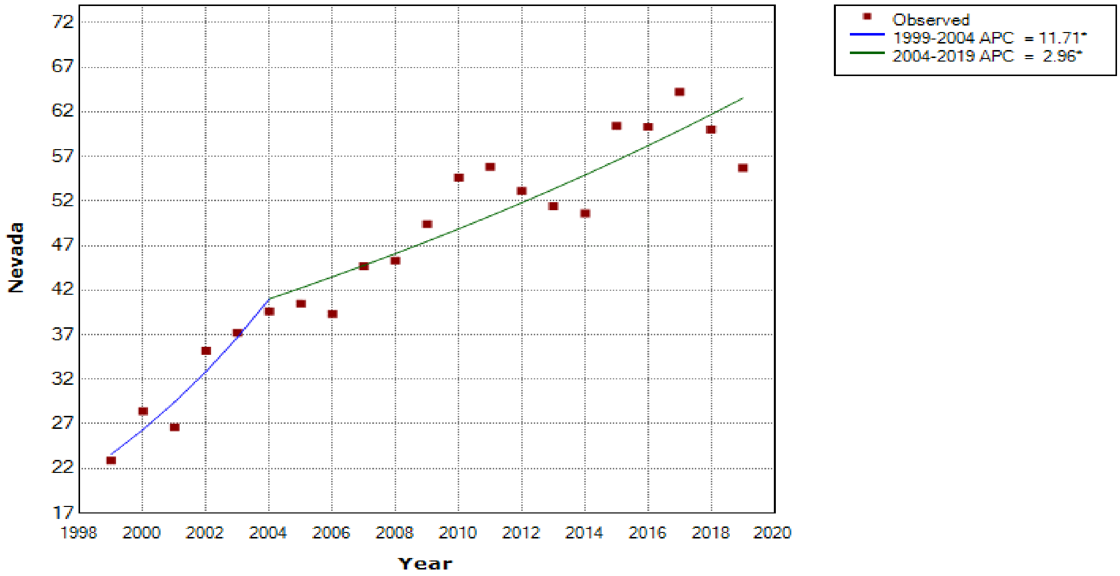
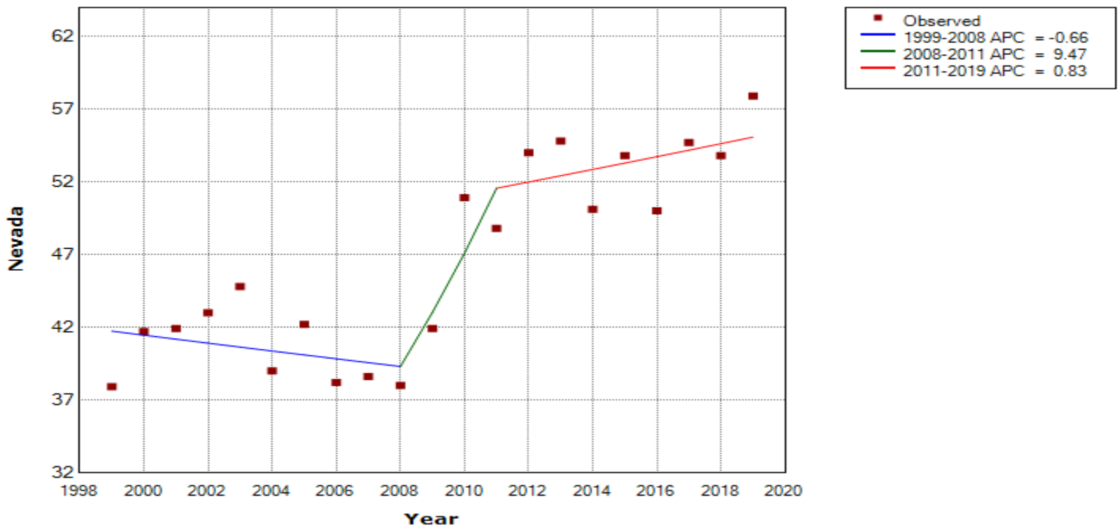


Figure 43. Trends of DoD in Nevada





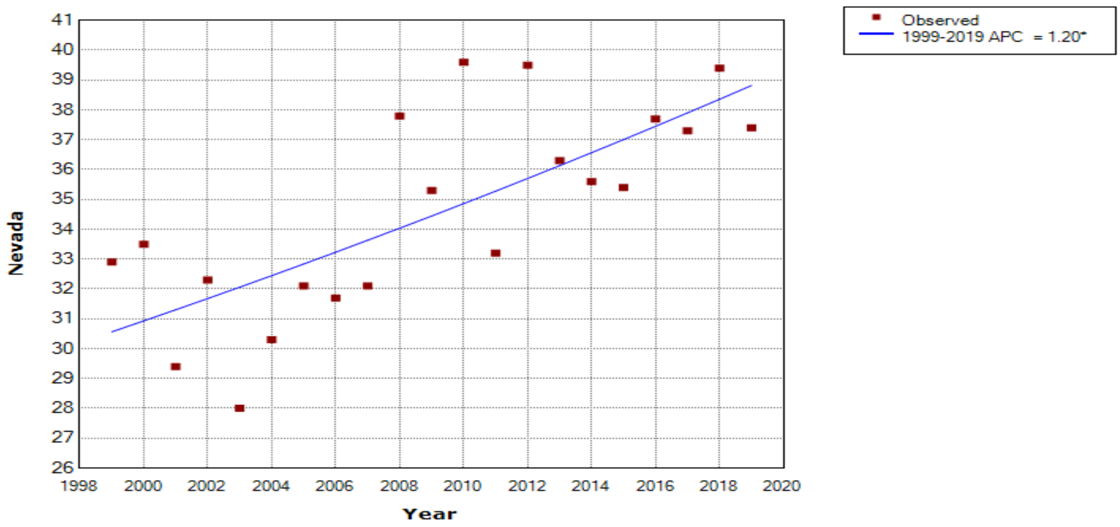
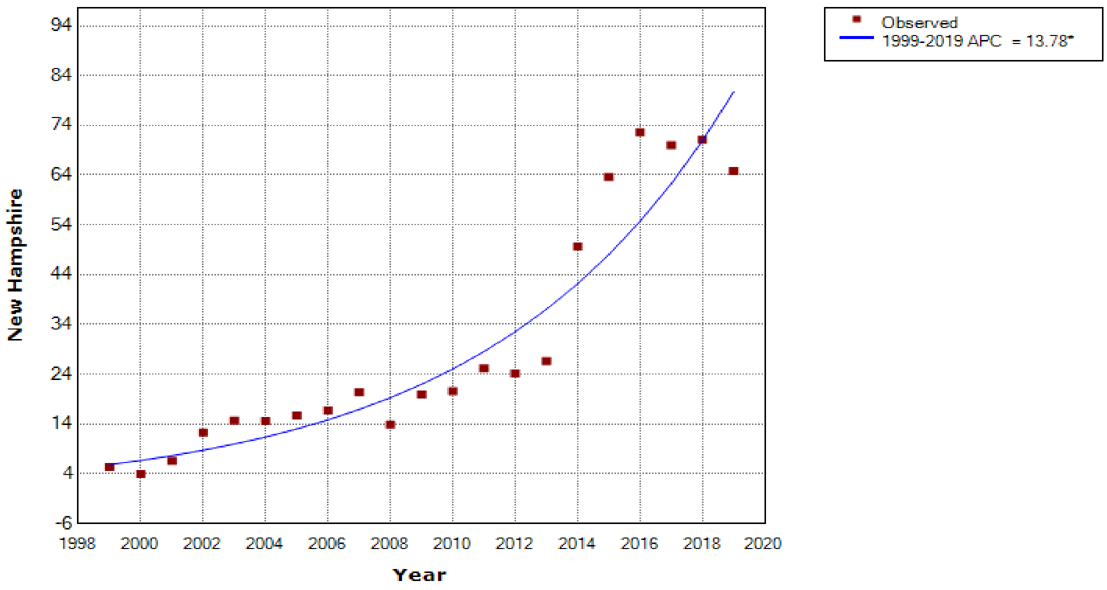
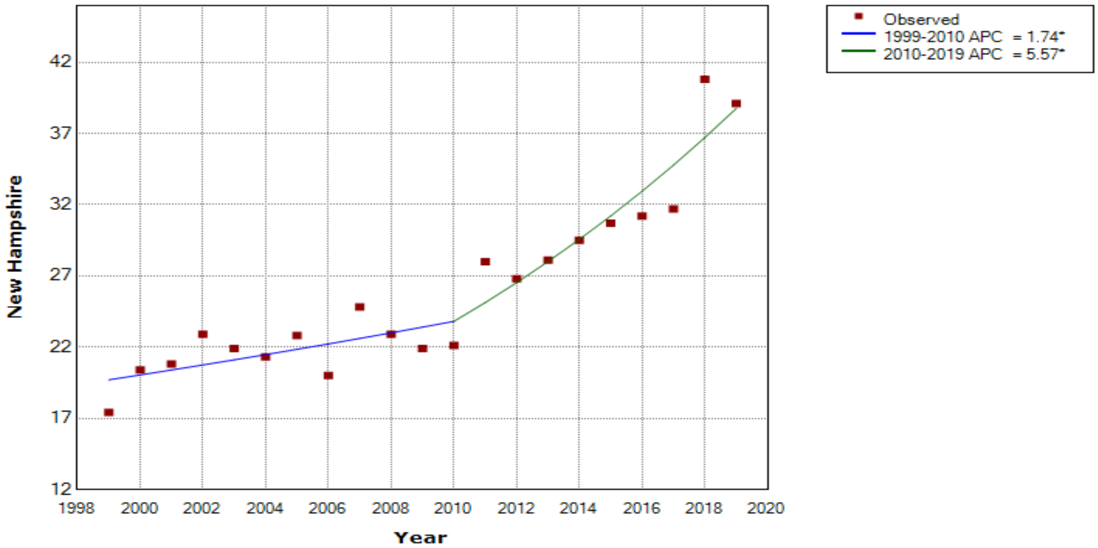


Figure 44. Trends of DoD in New Hampshire





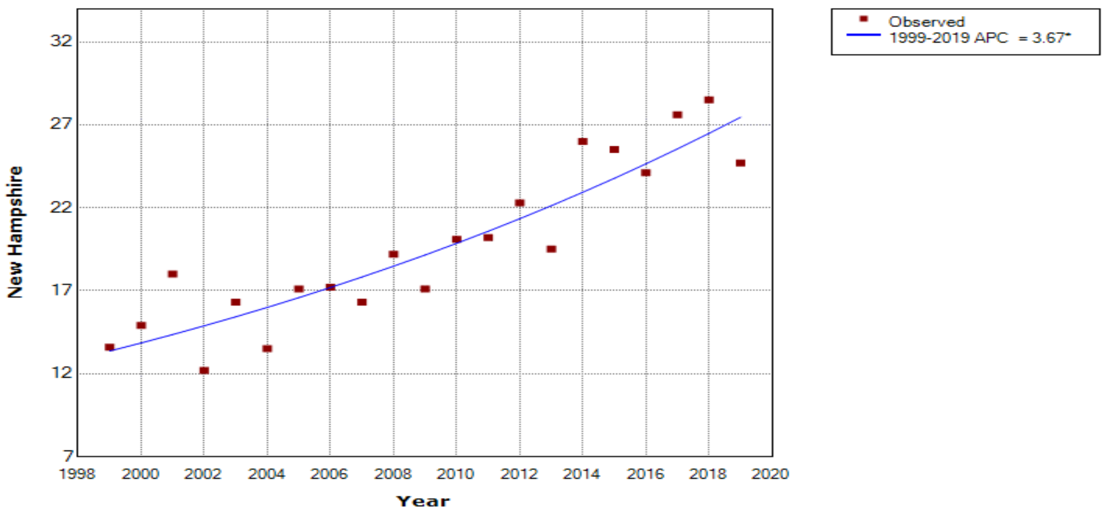


Figure 45. Trends of DoD in New Jersey

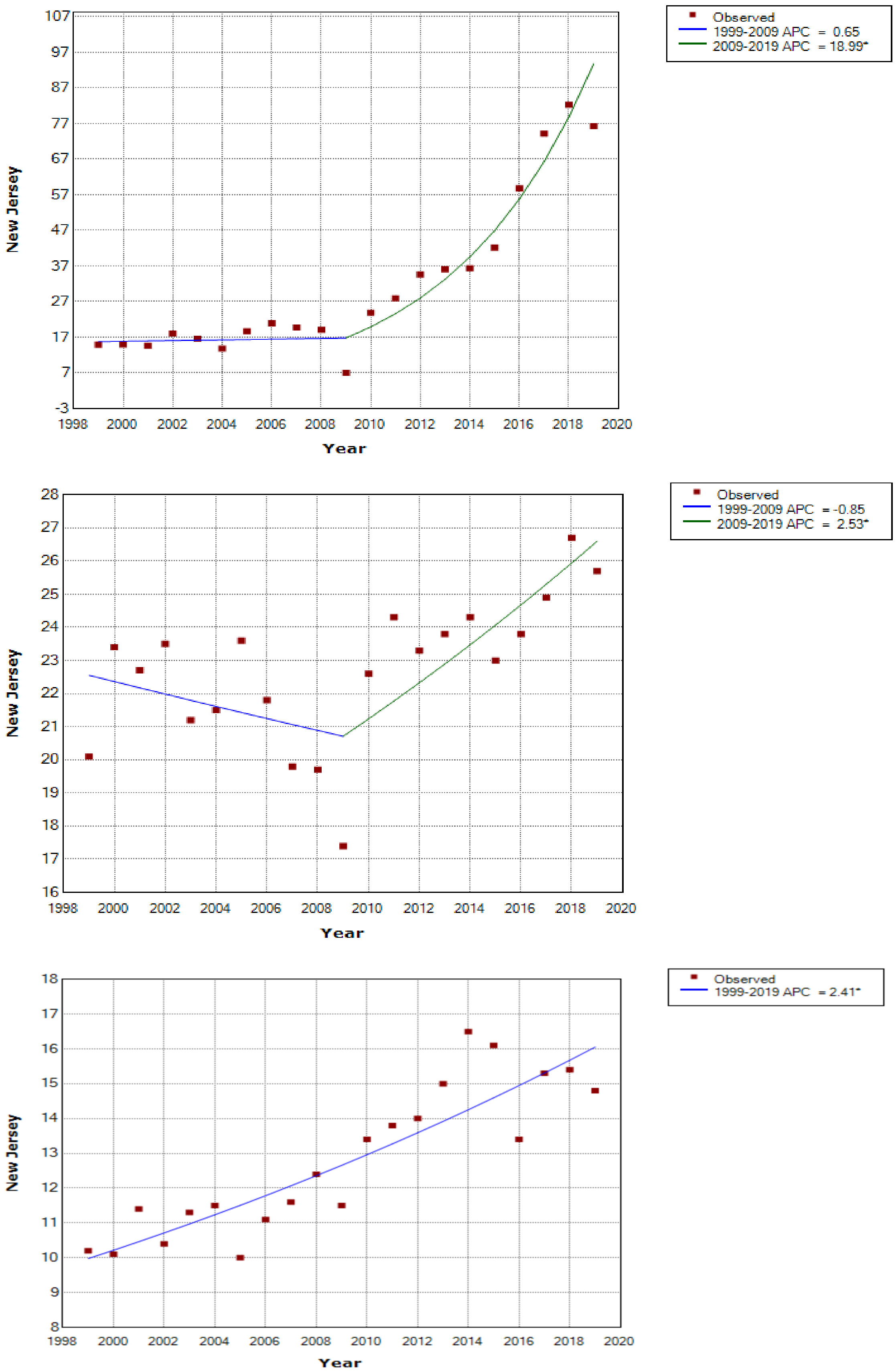
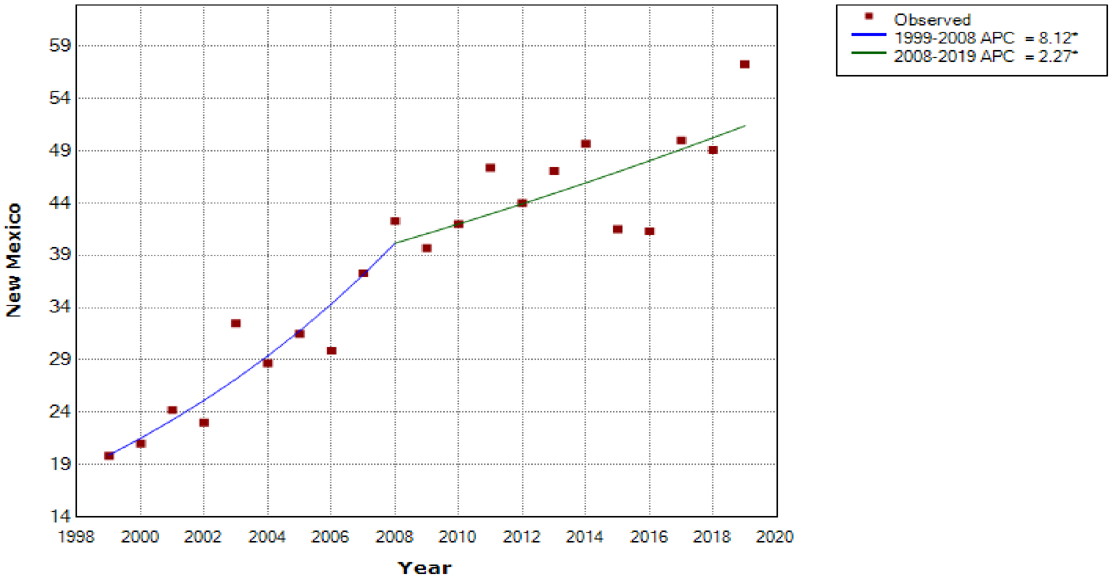
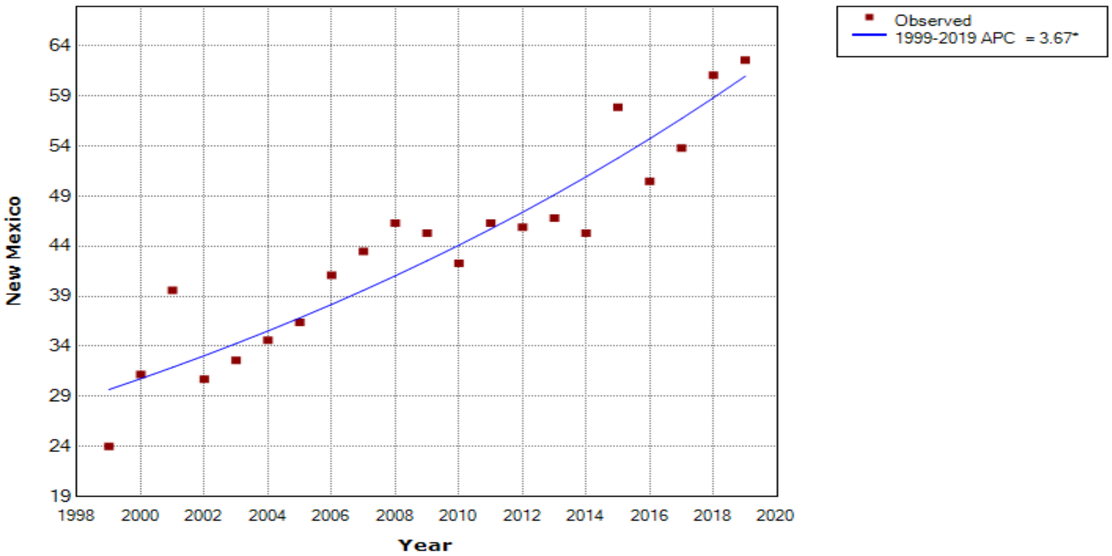


Figure 46. Trends of DoD in New Mexico





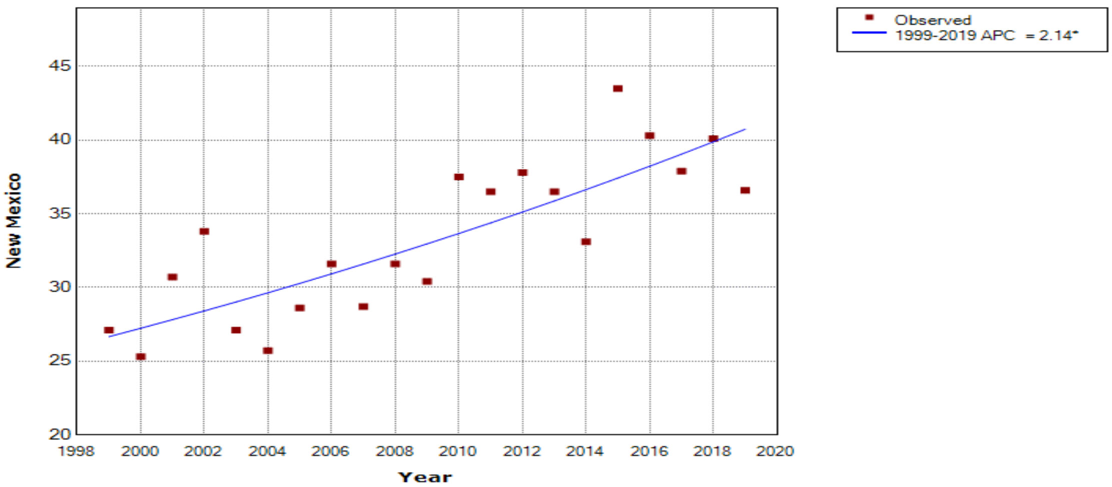
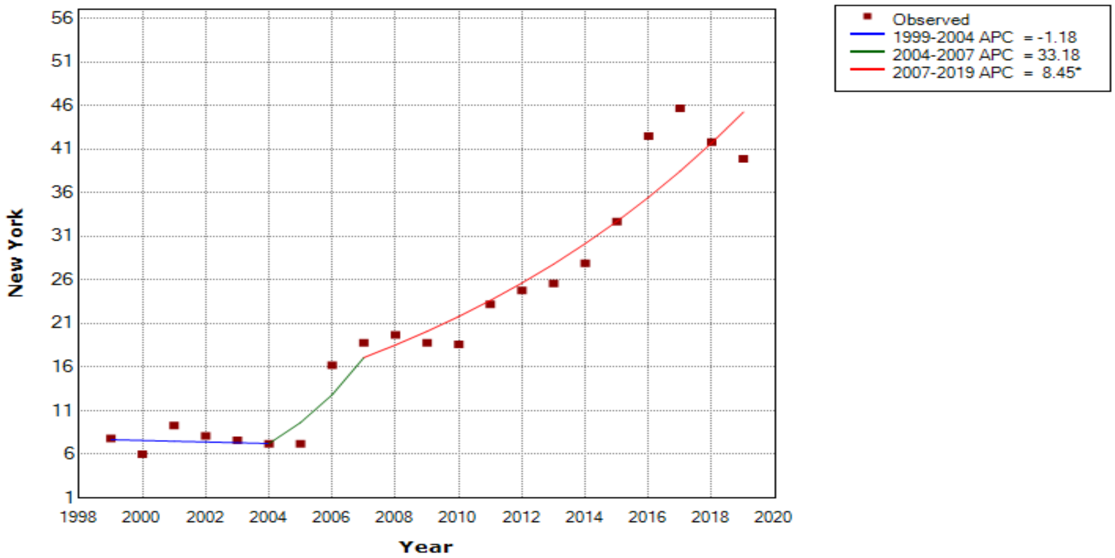
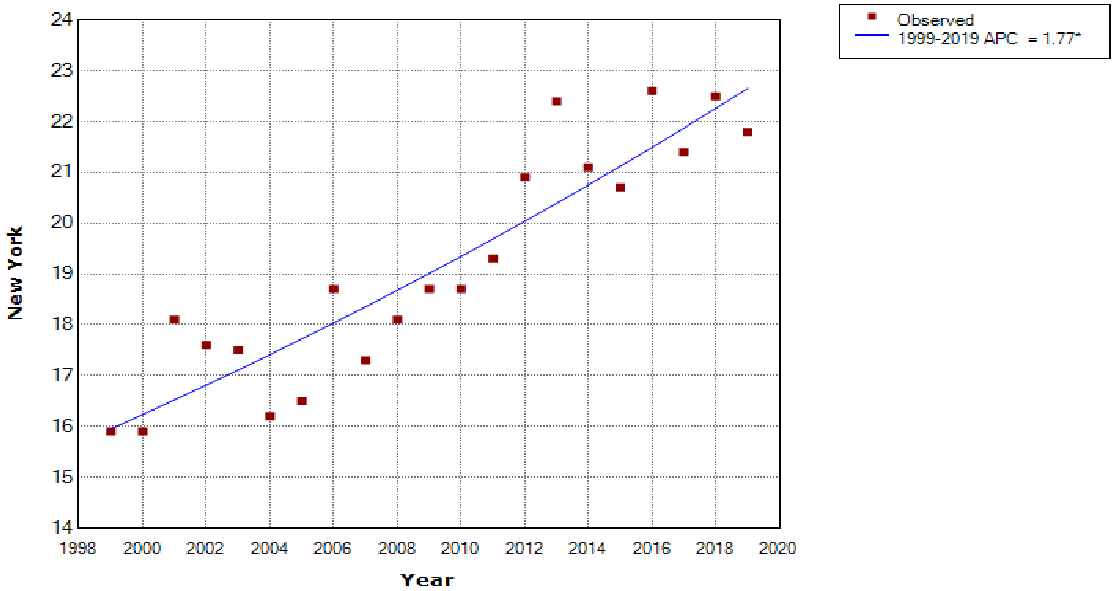


Figure 47. Trends of DoD in New York





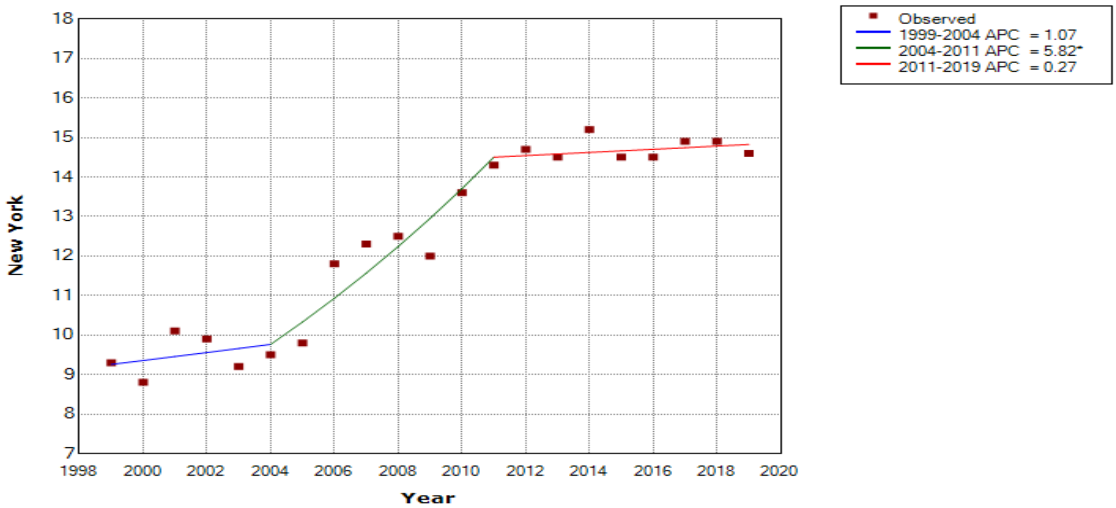
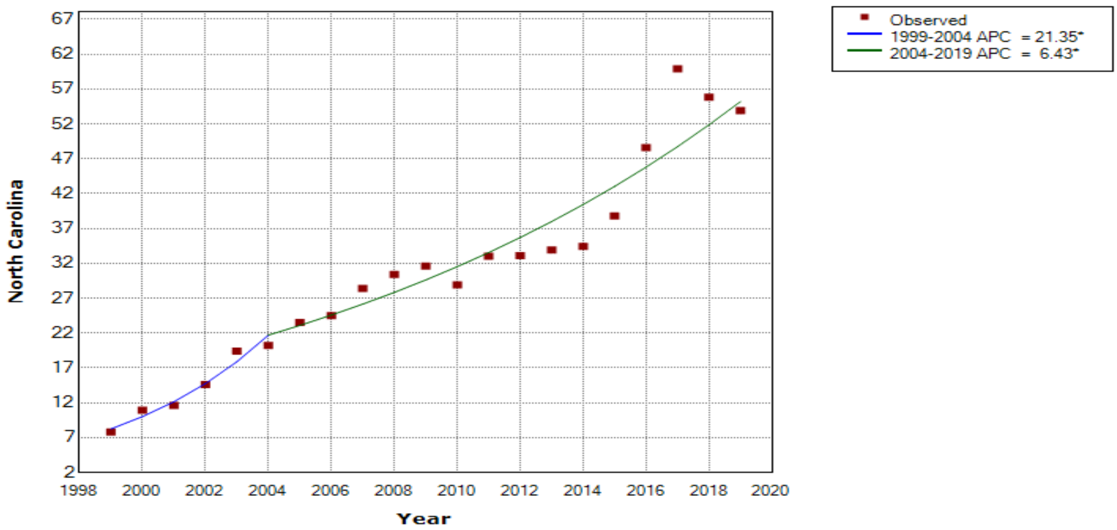
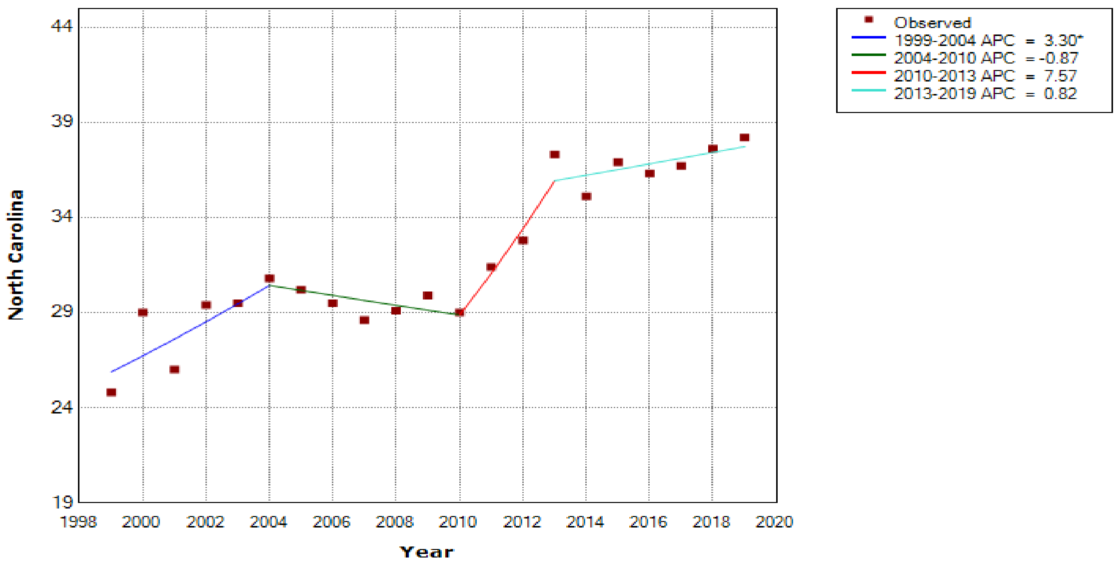


Figure 48. Trends of DoD in North Carolina





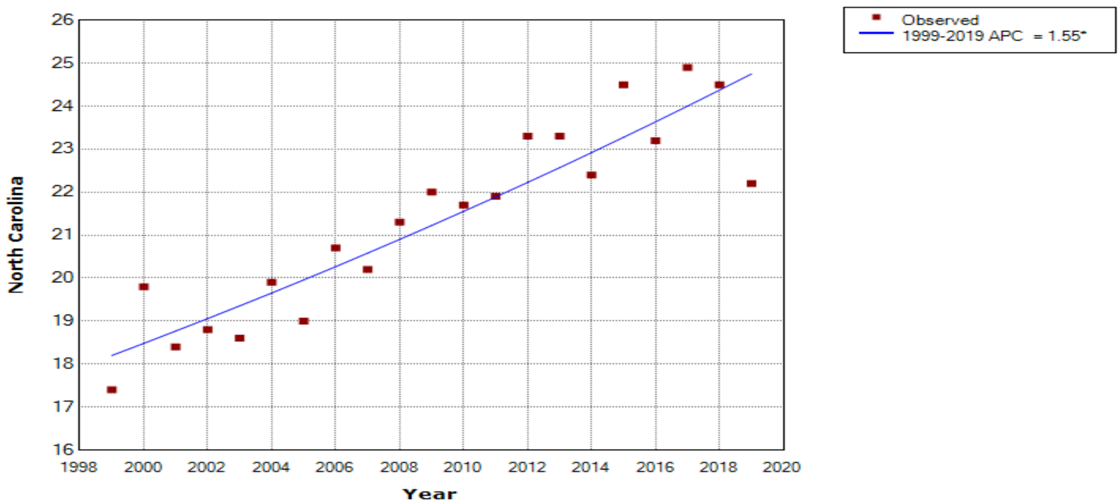


Figure 49. Trends of DoD in North Dakota

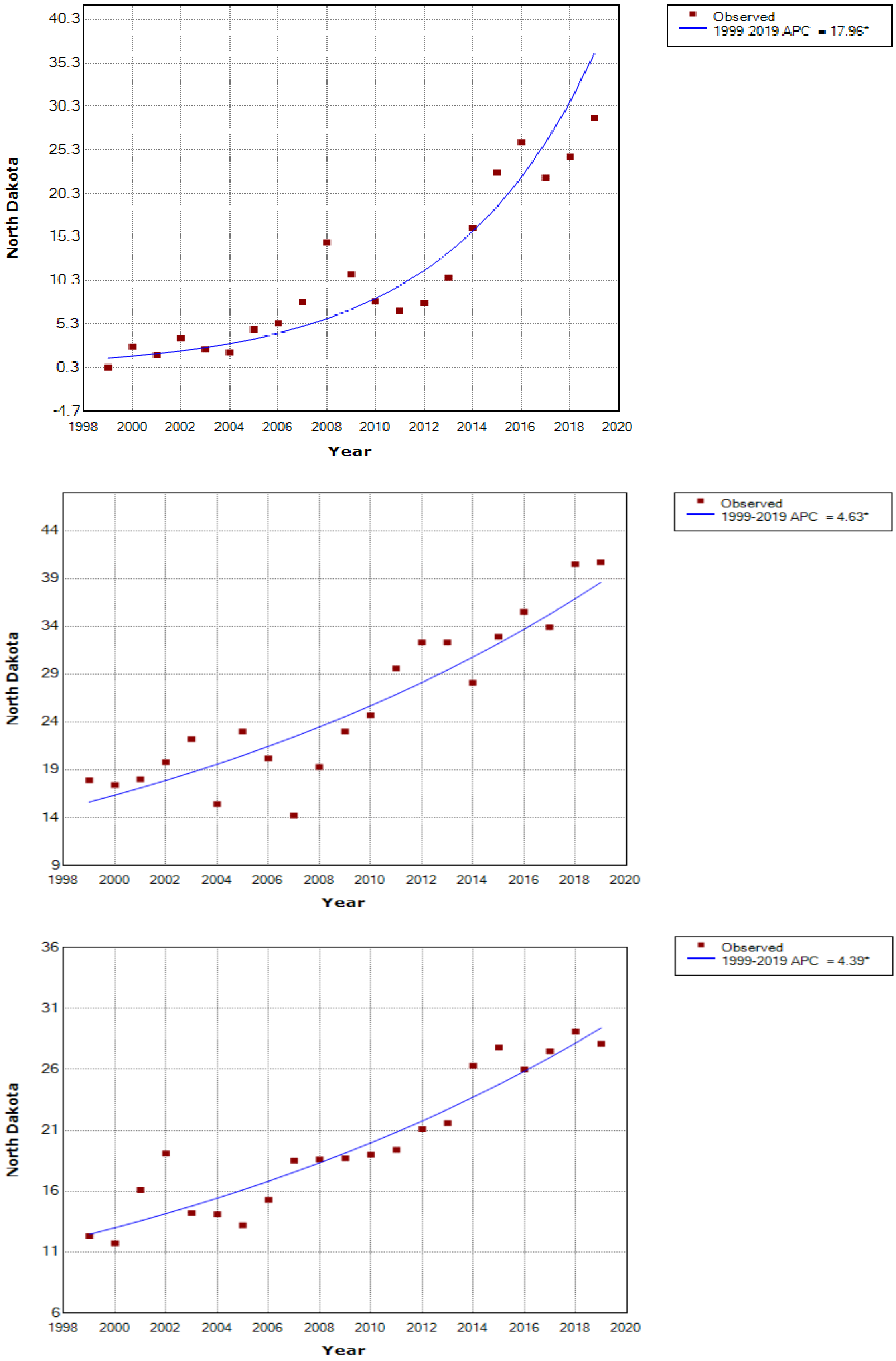
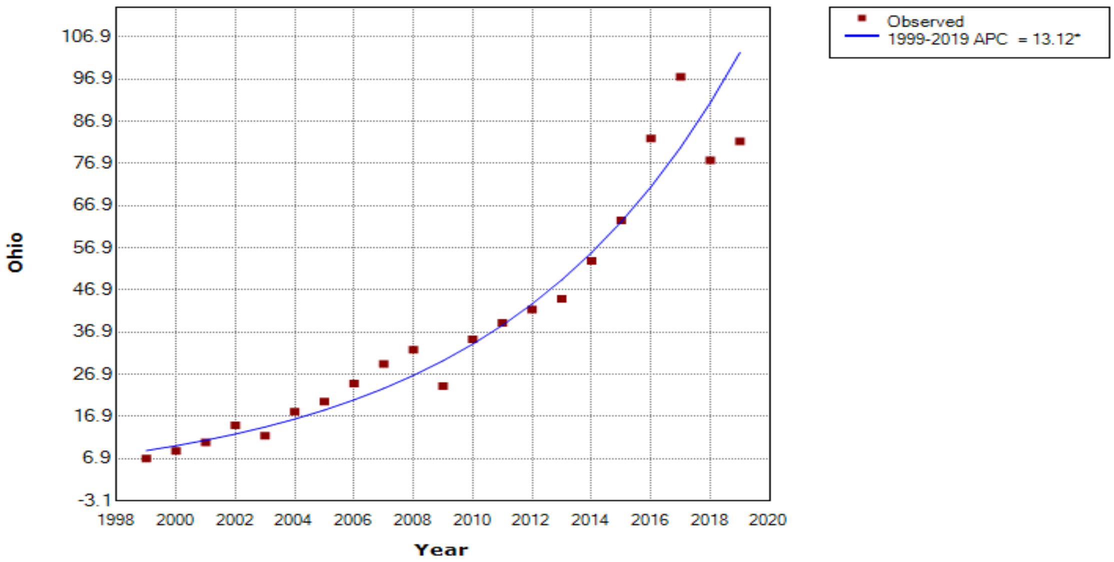
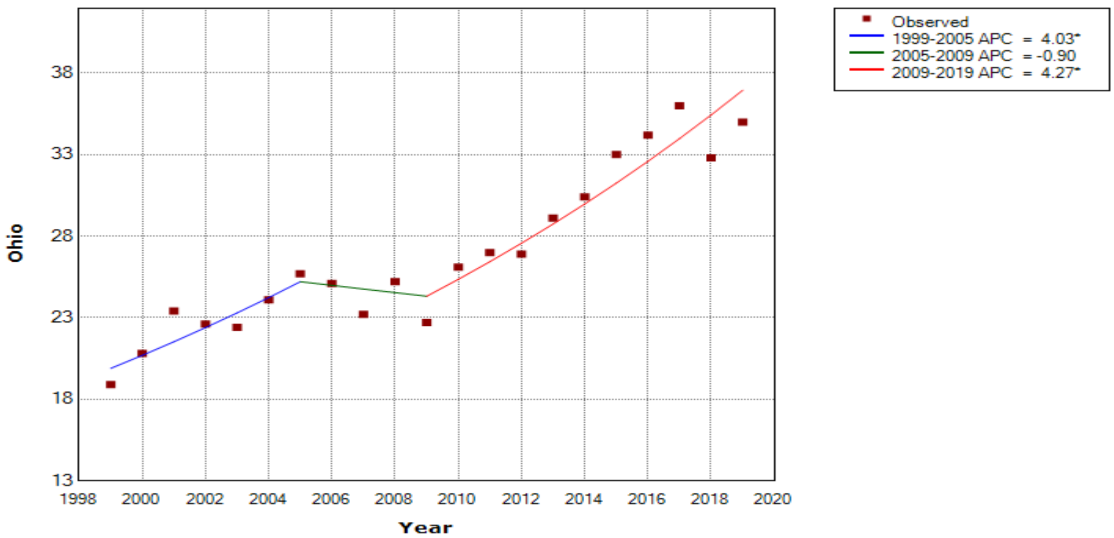


Figure 50. Trends of DoD in Ohio





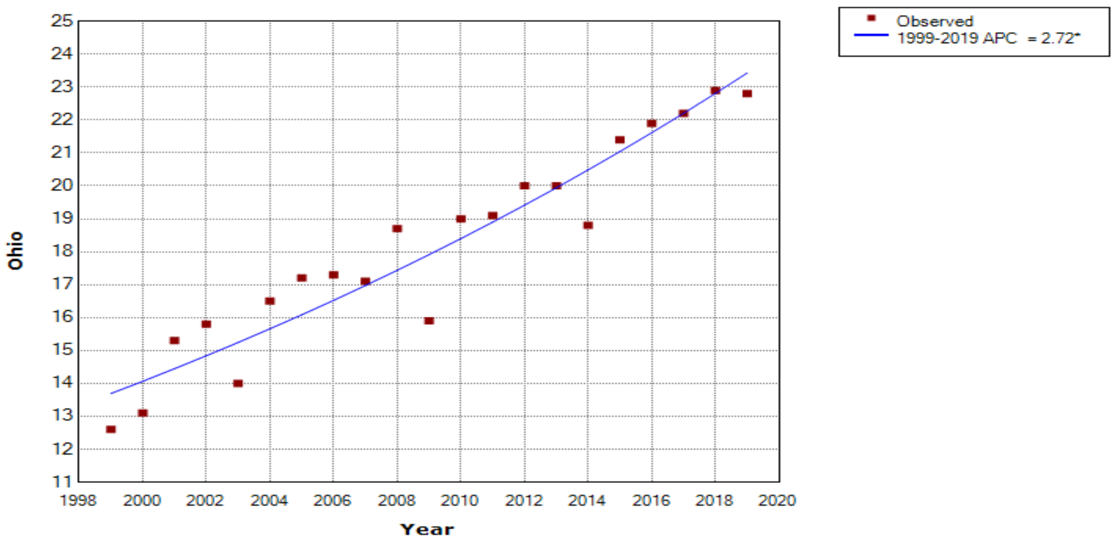
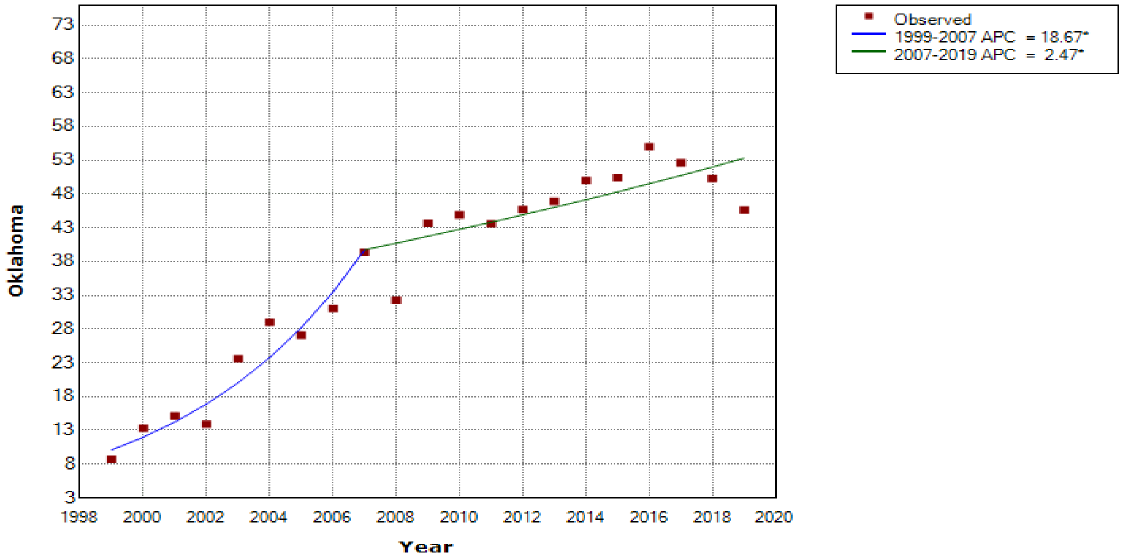
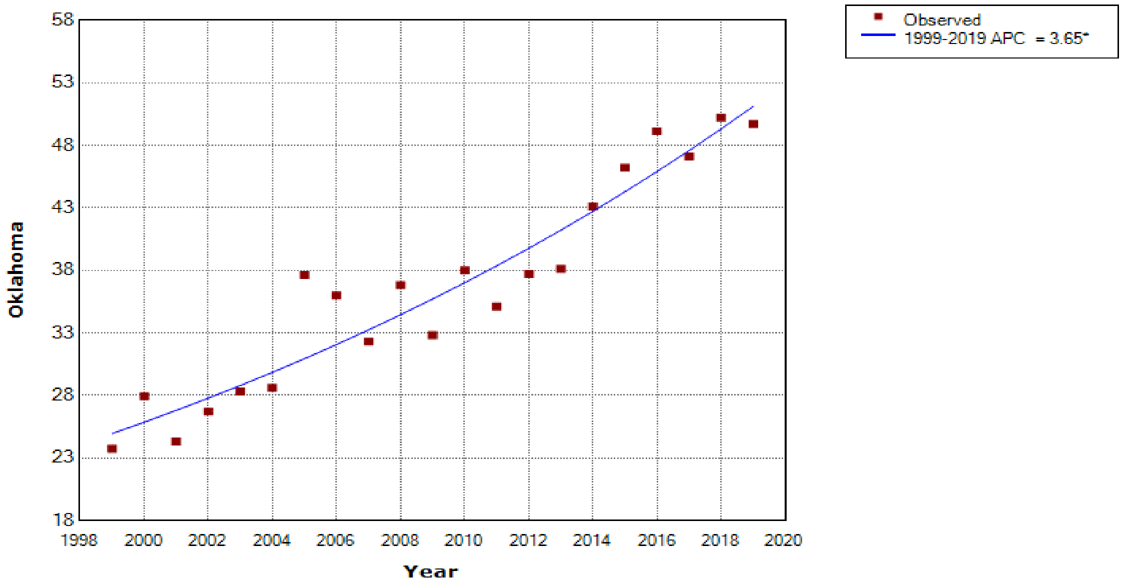


Figure 51. Trends of DoD in Oklahoma





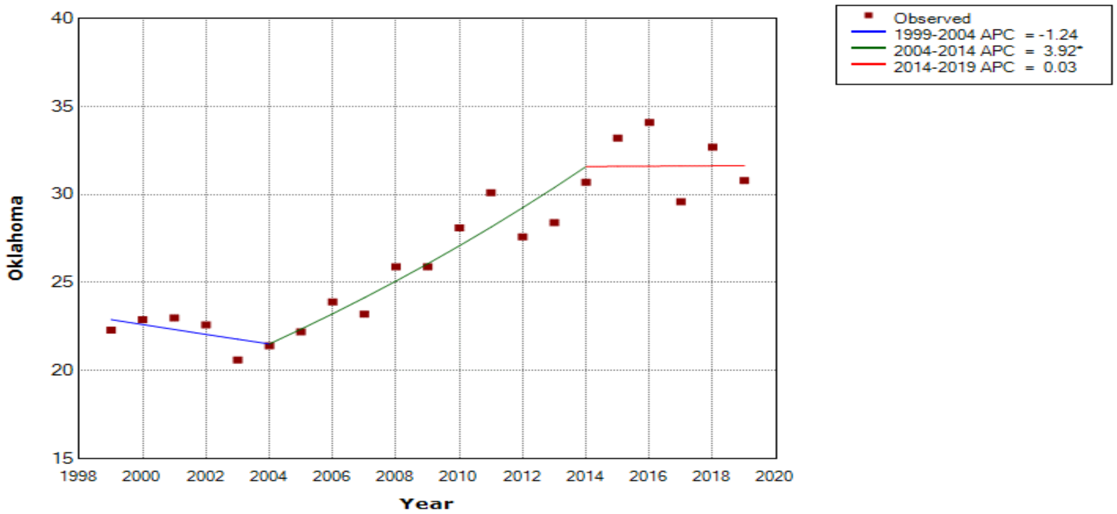
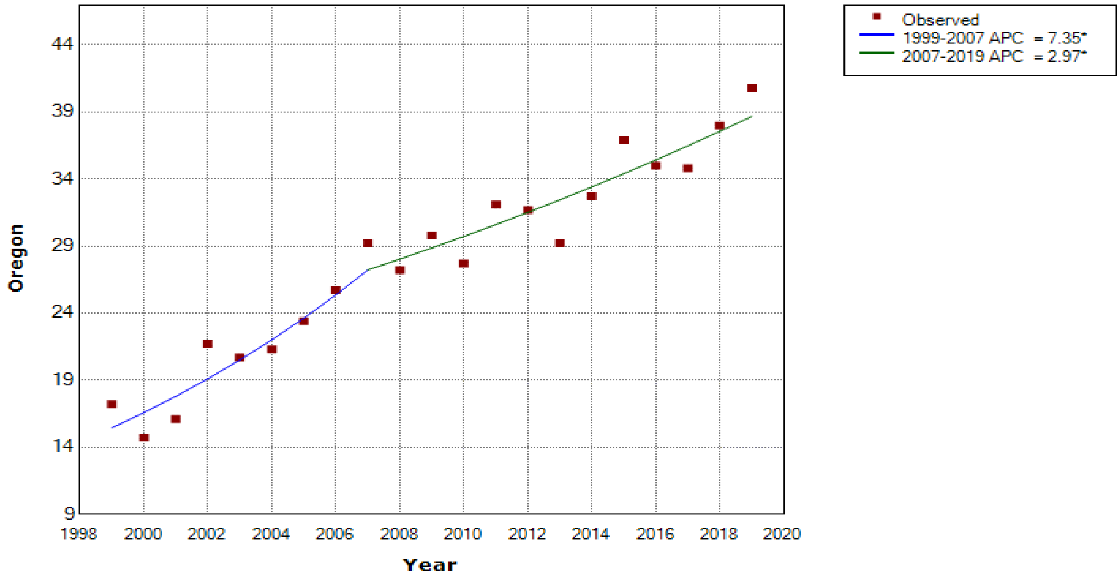
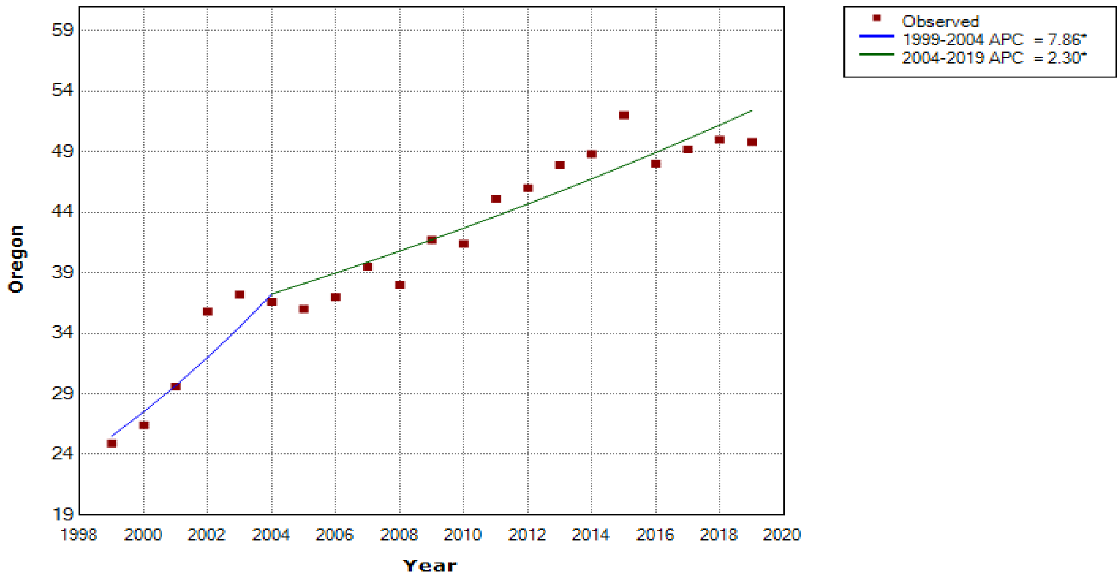


Figure 52. Trends of DoD in Oregon





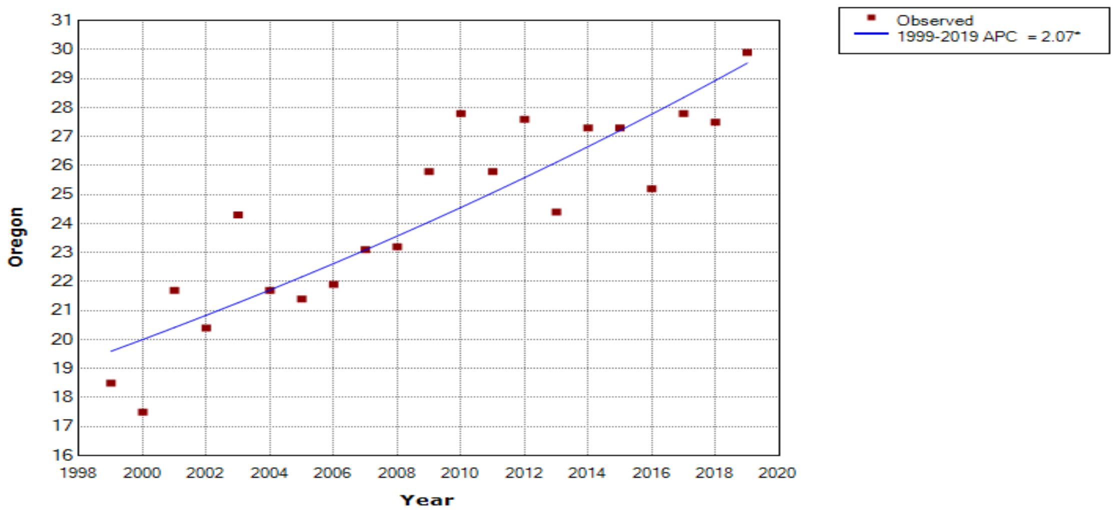
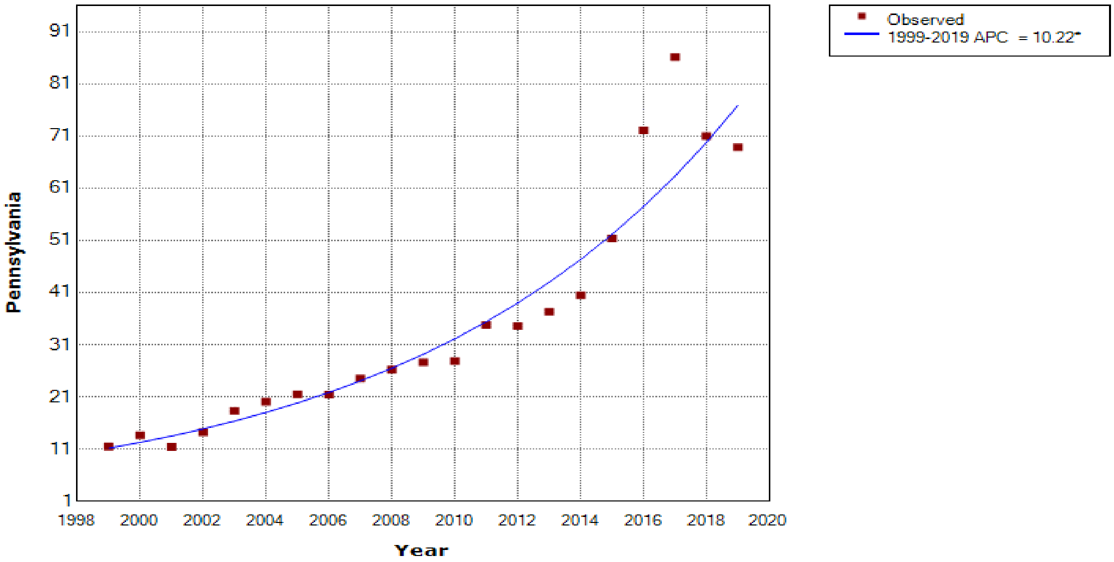
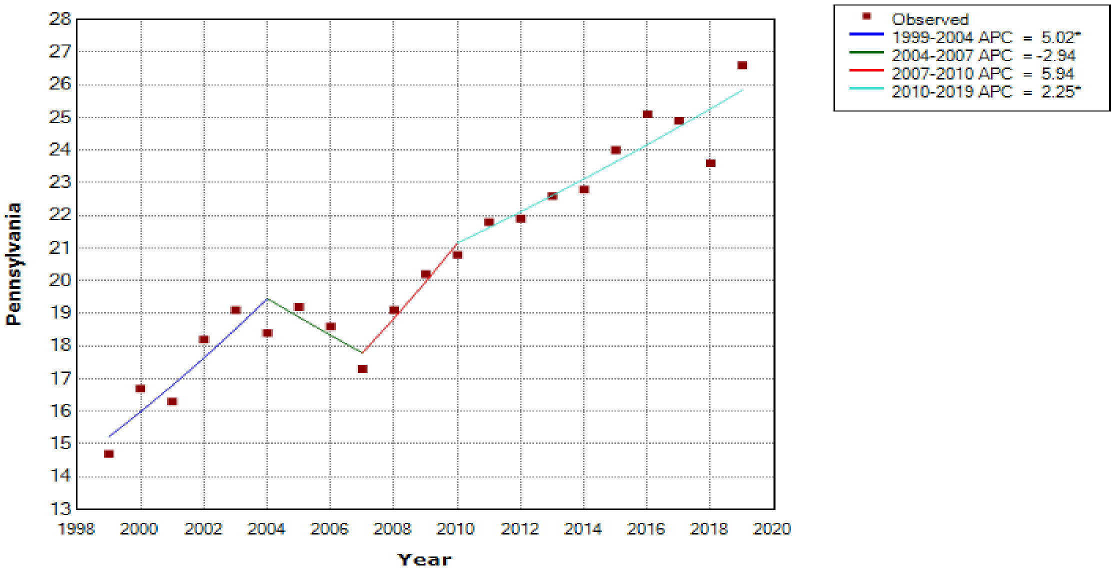


Figure 53. Trends of DoD in Pennsylvania





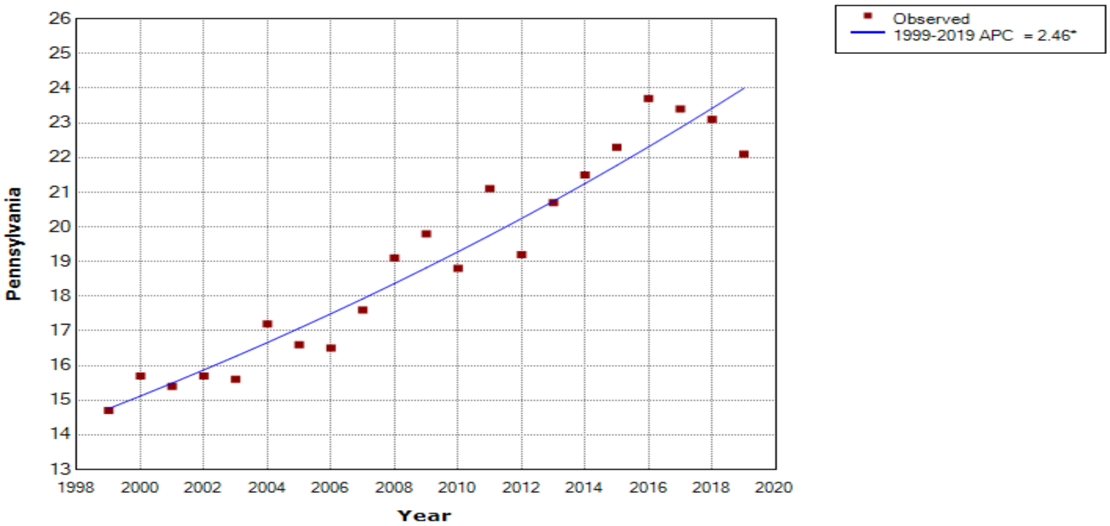
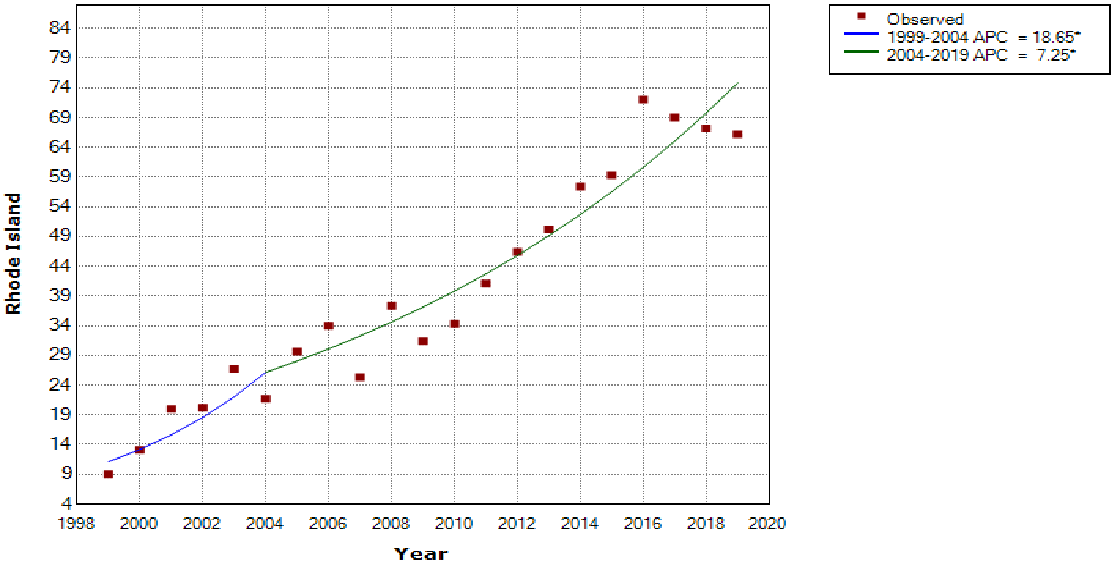
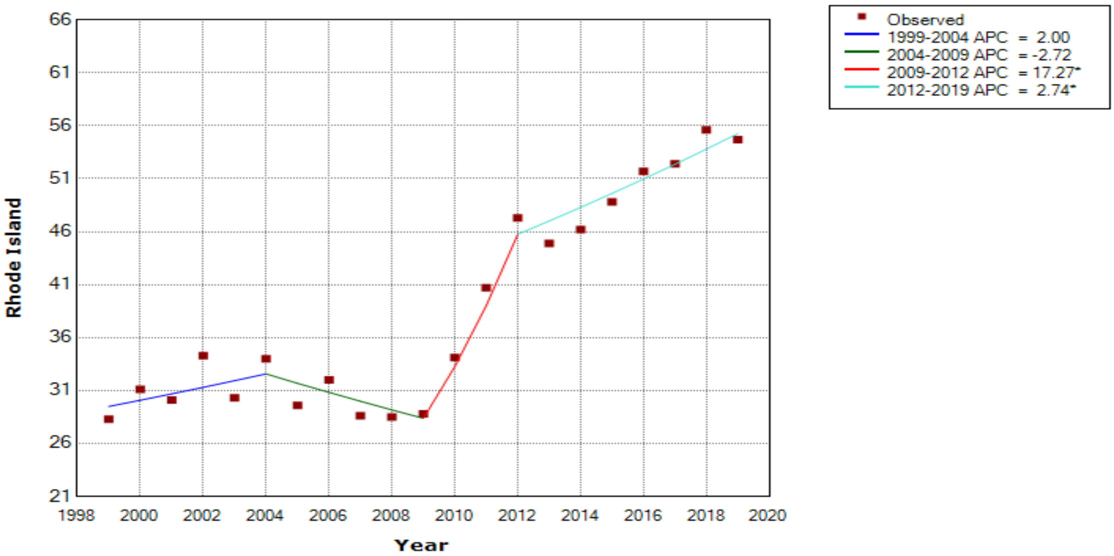


Figure 54. Trends of DoD in Rhode Island





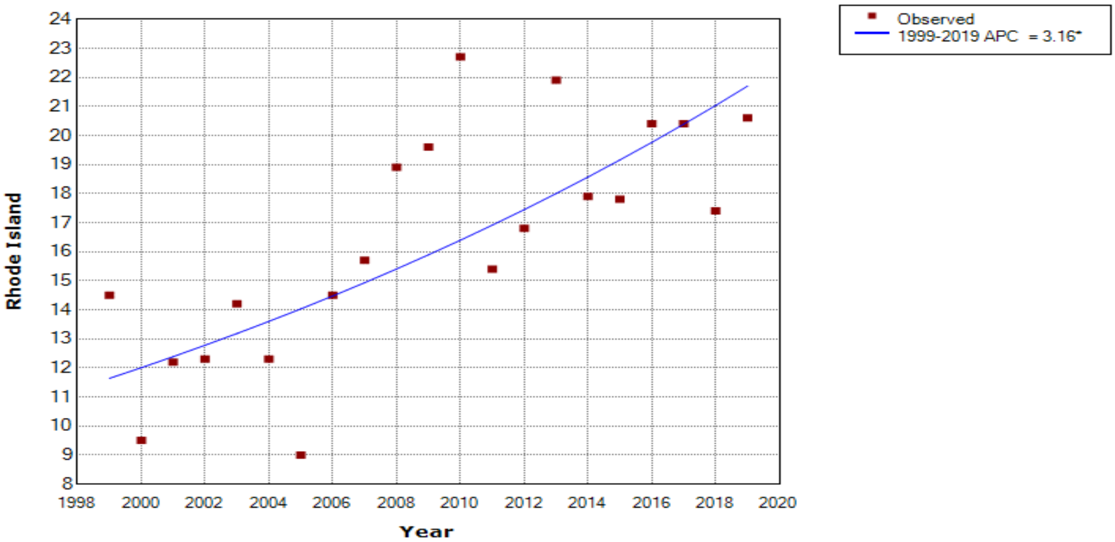


Figure 55. Trends of DoD in South Carolina

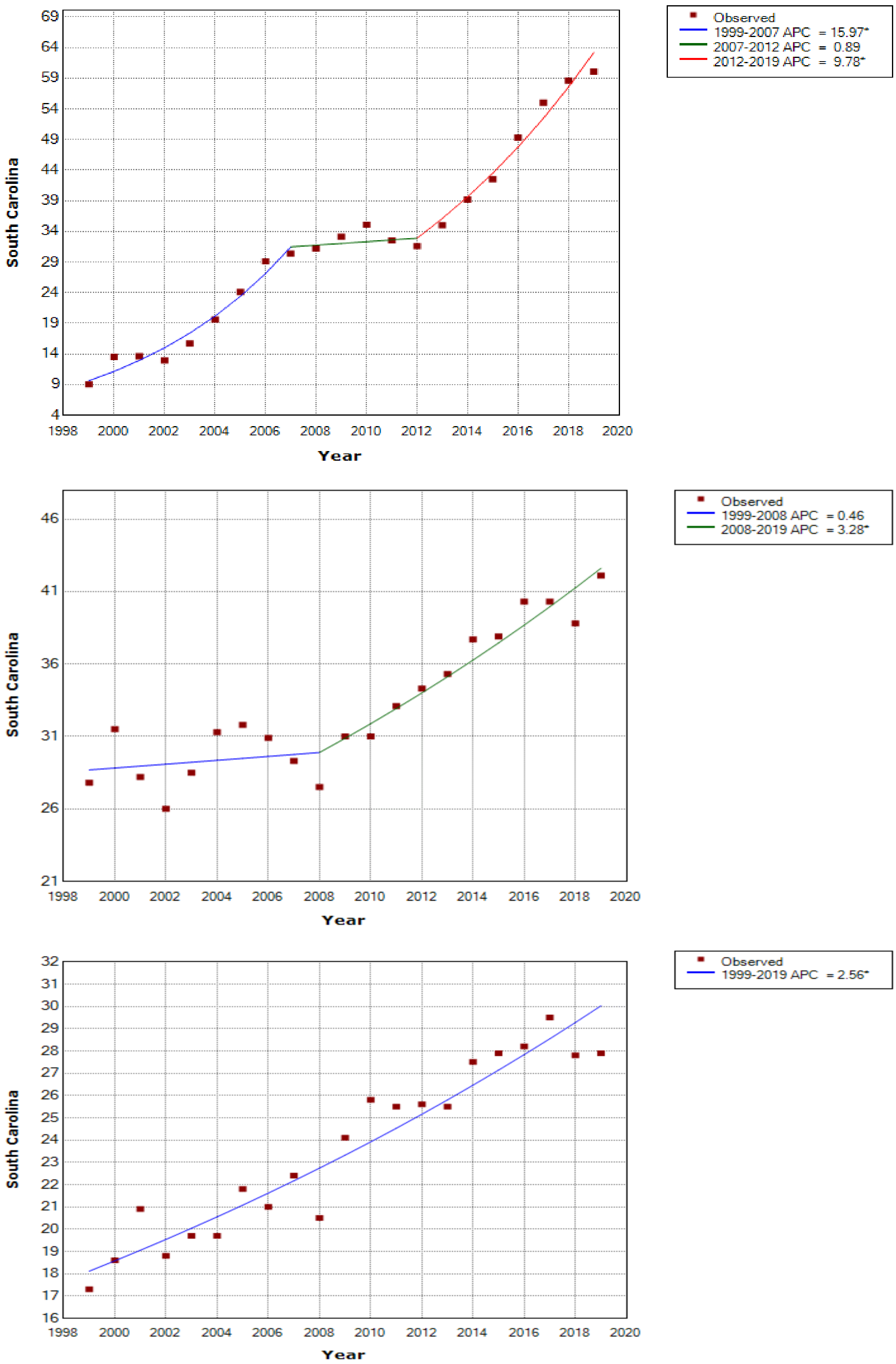
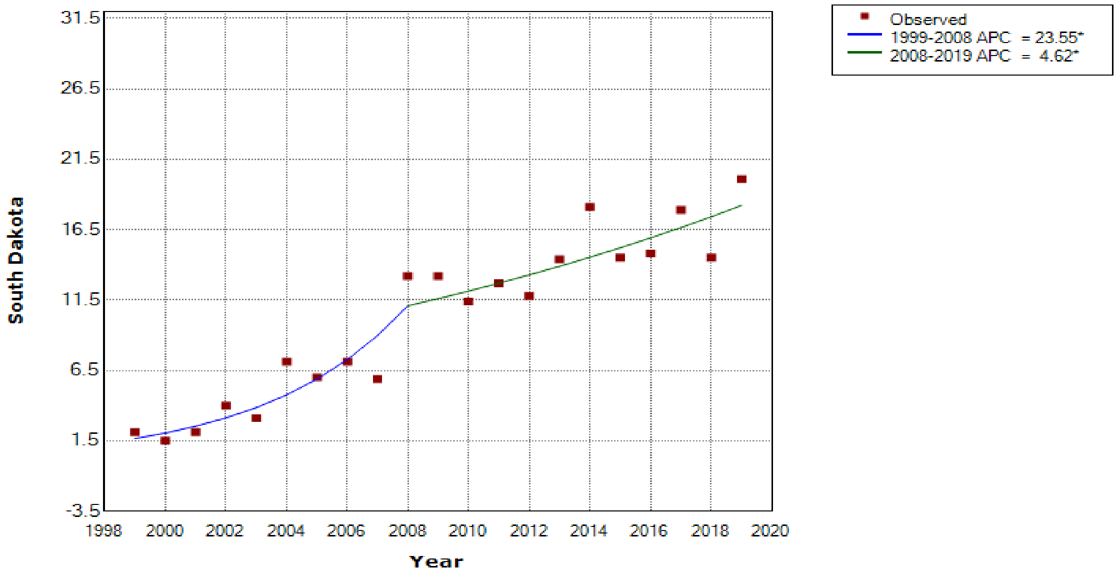
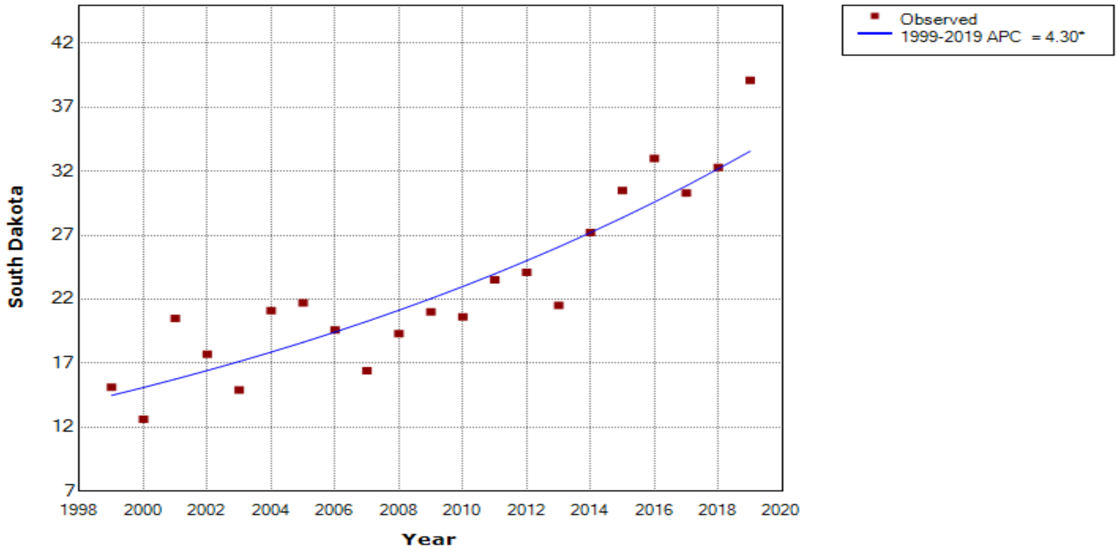


Figure 56. Trends of DoD in South Dakota





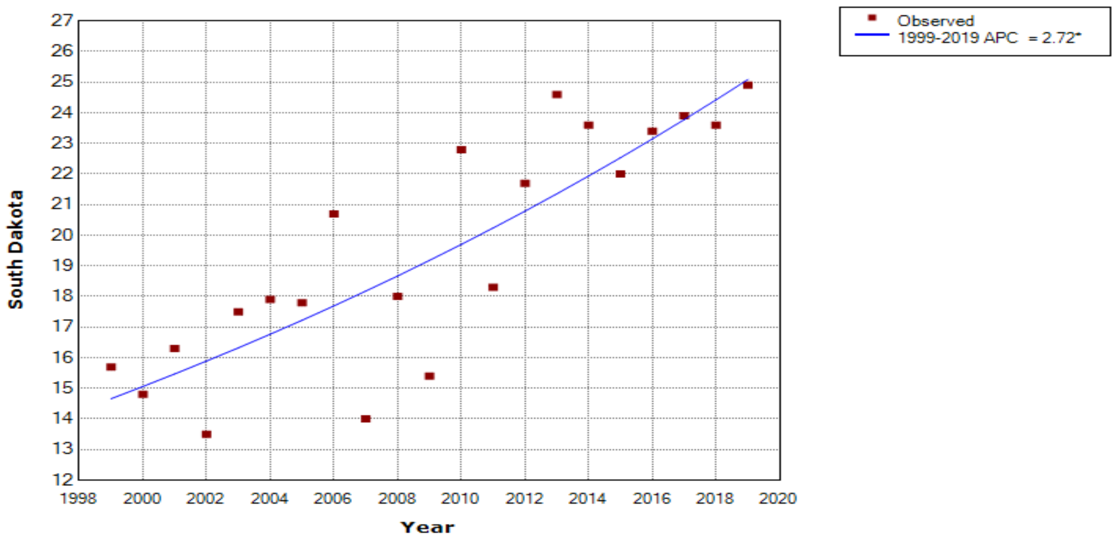
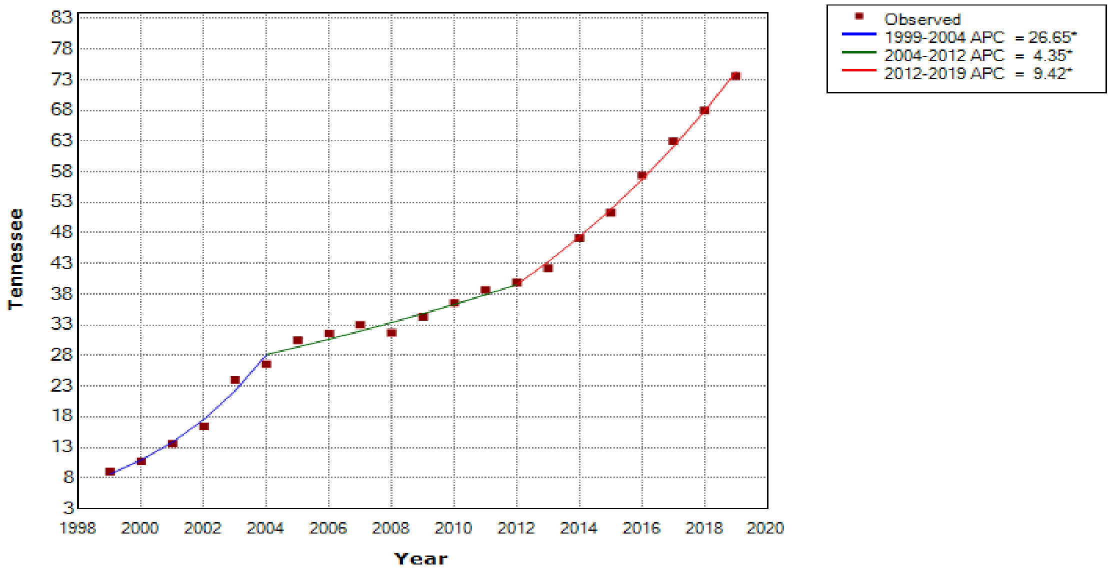
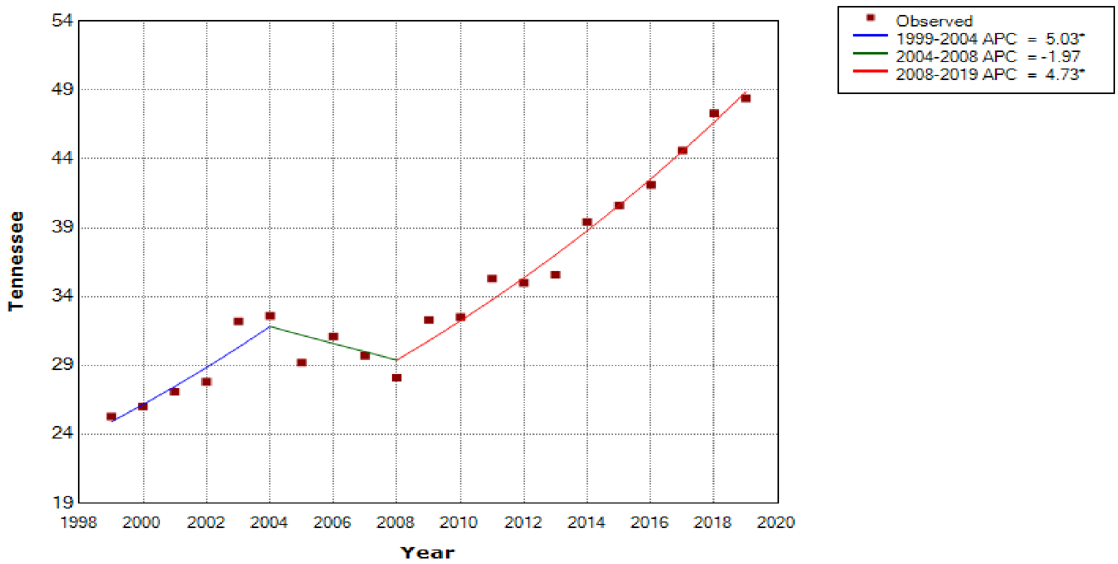


Figure 57. Trends of DoD in Tennessee





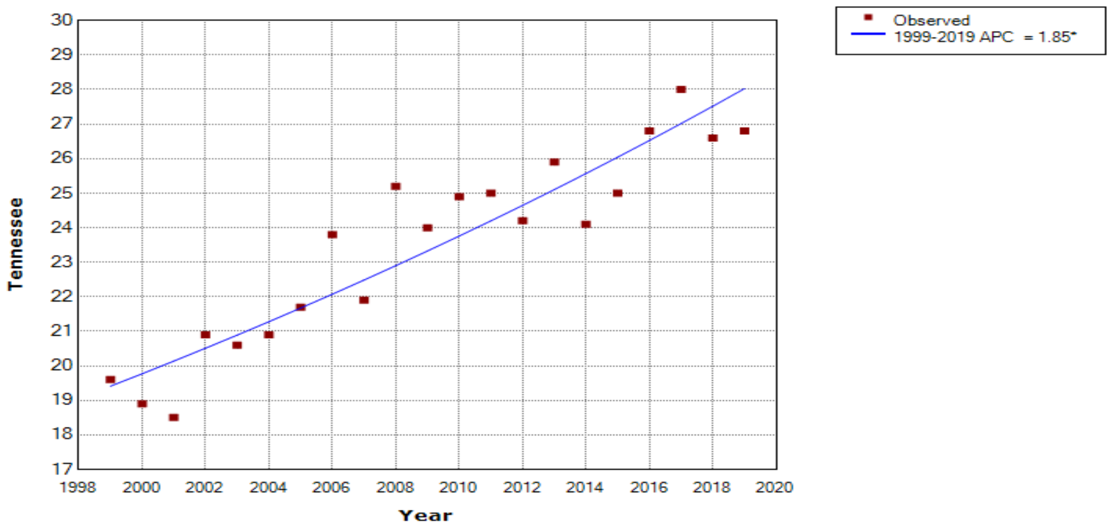
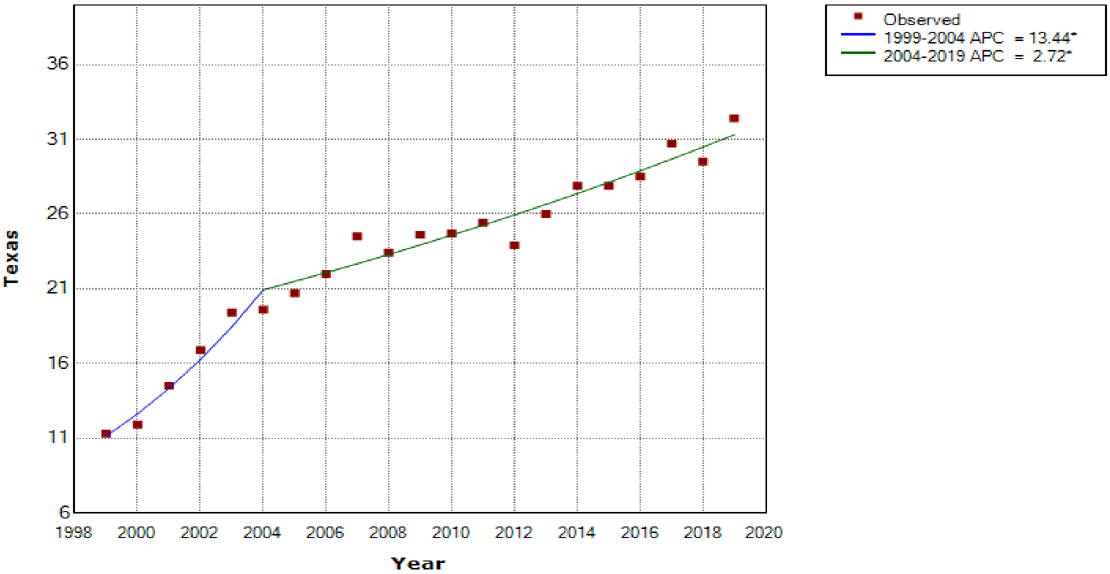
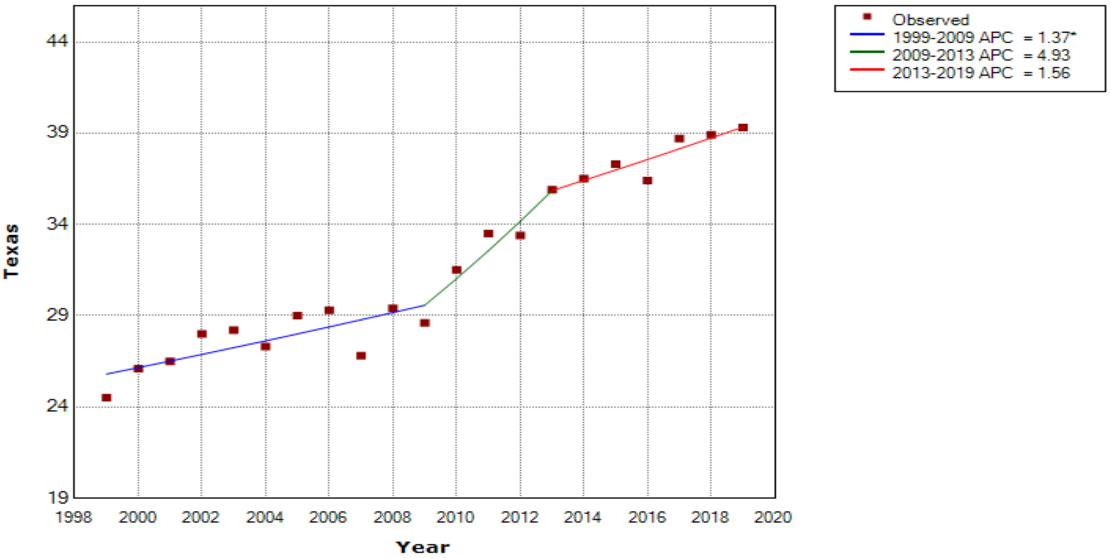


Figure 58. Trends of DoD in Texas





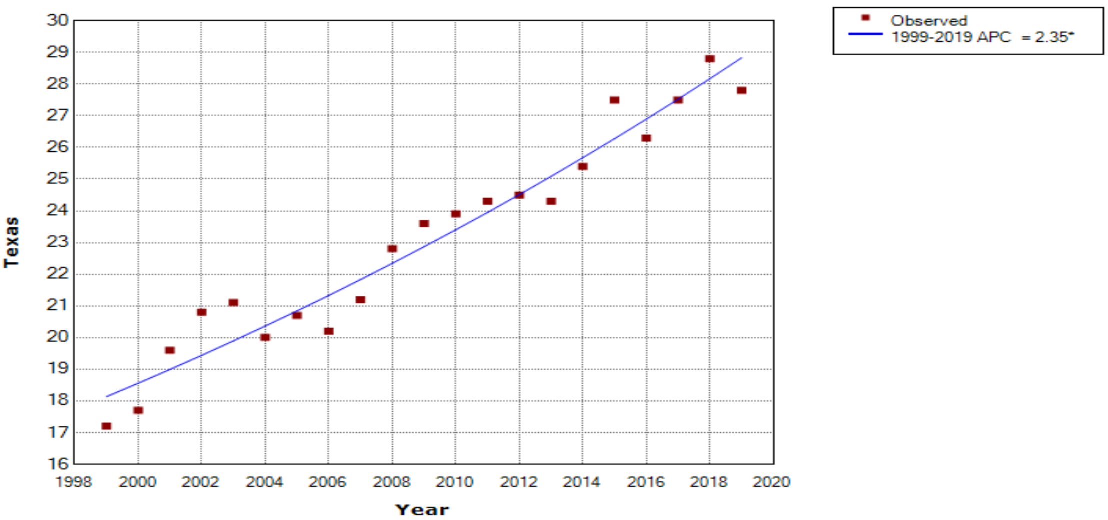
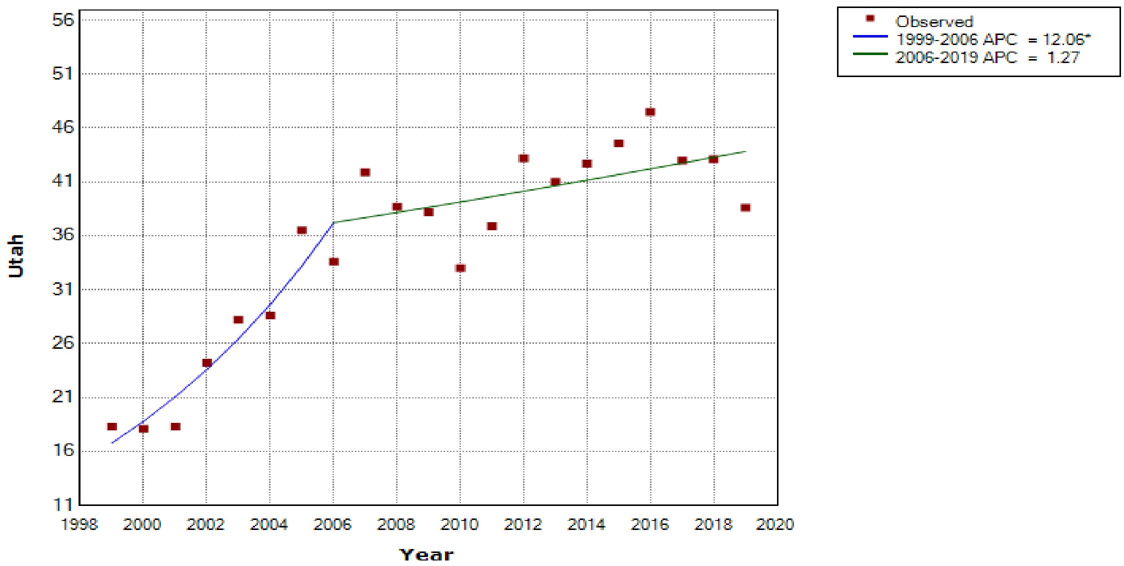
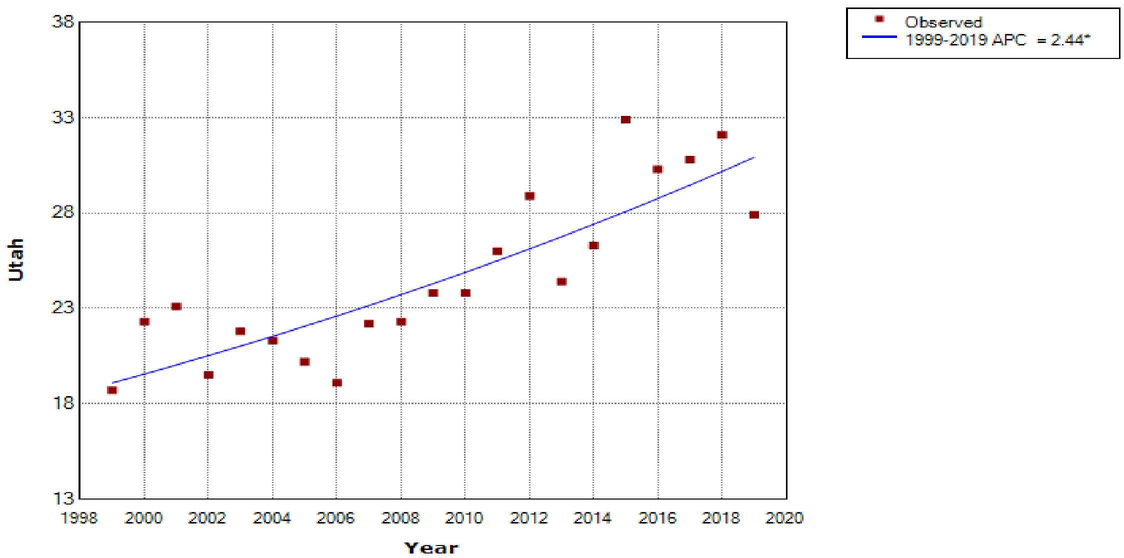


Figure 59. Trends of DoD in Utah





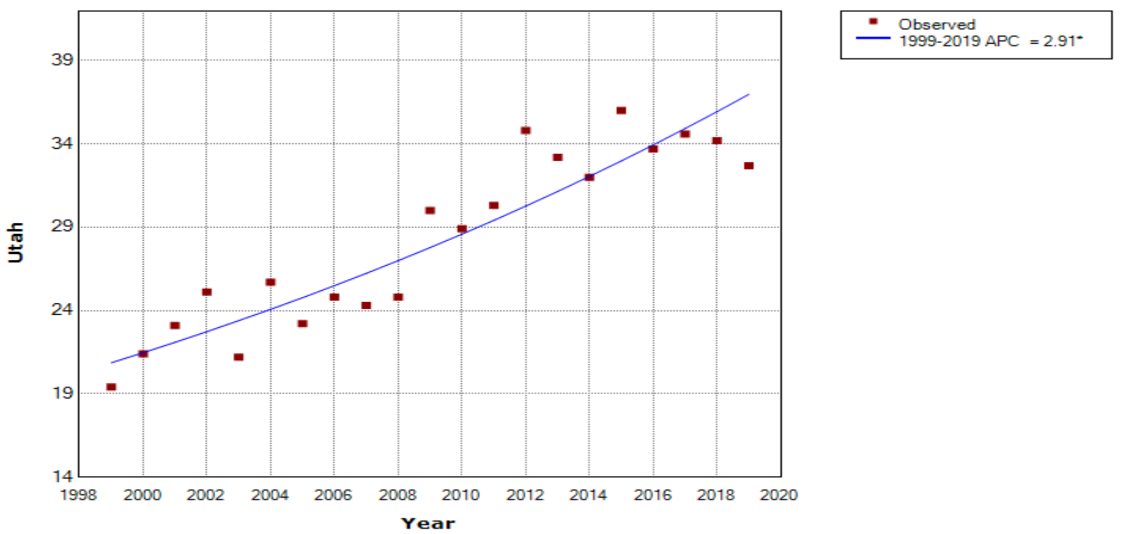
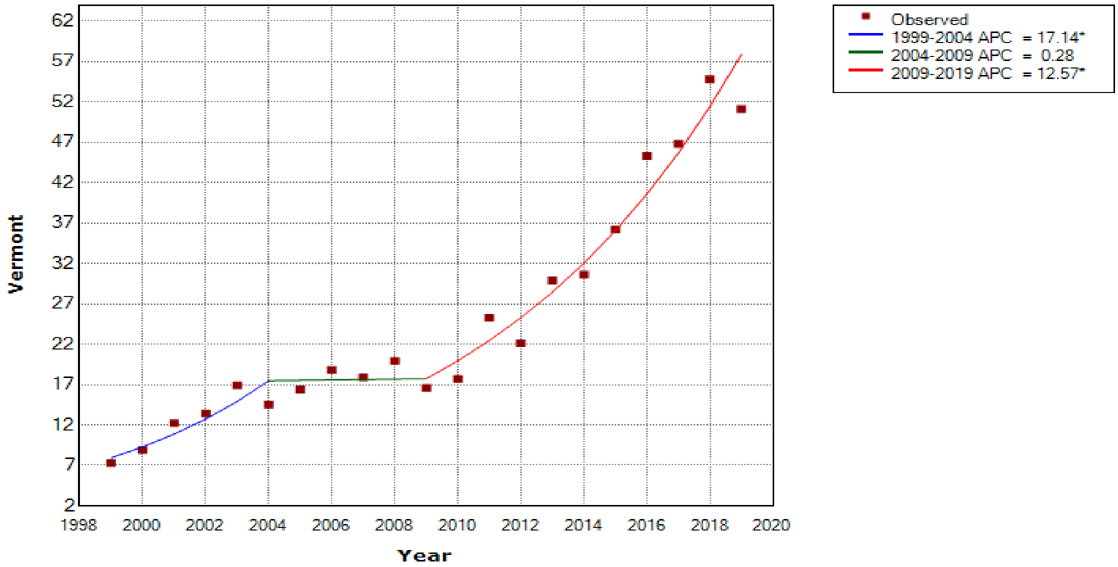
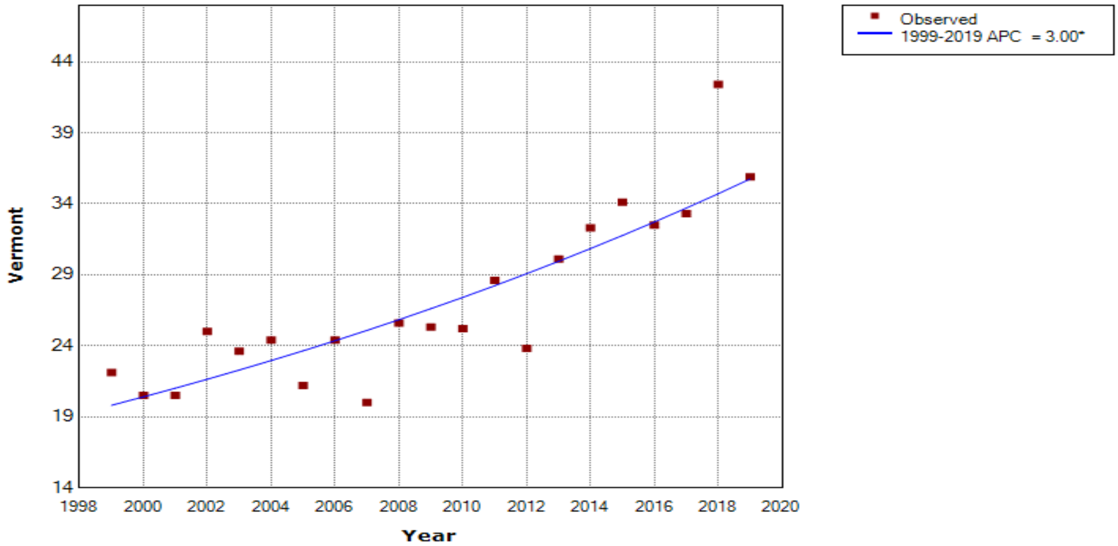


Figure 60. Trends of DoD in Vermont





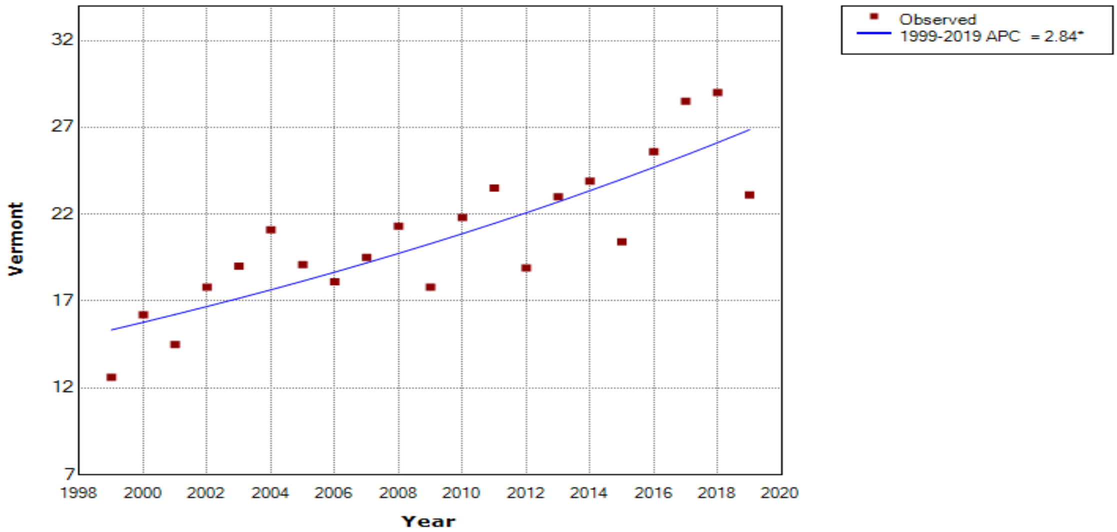
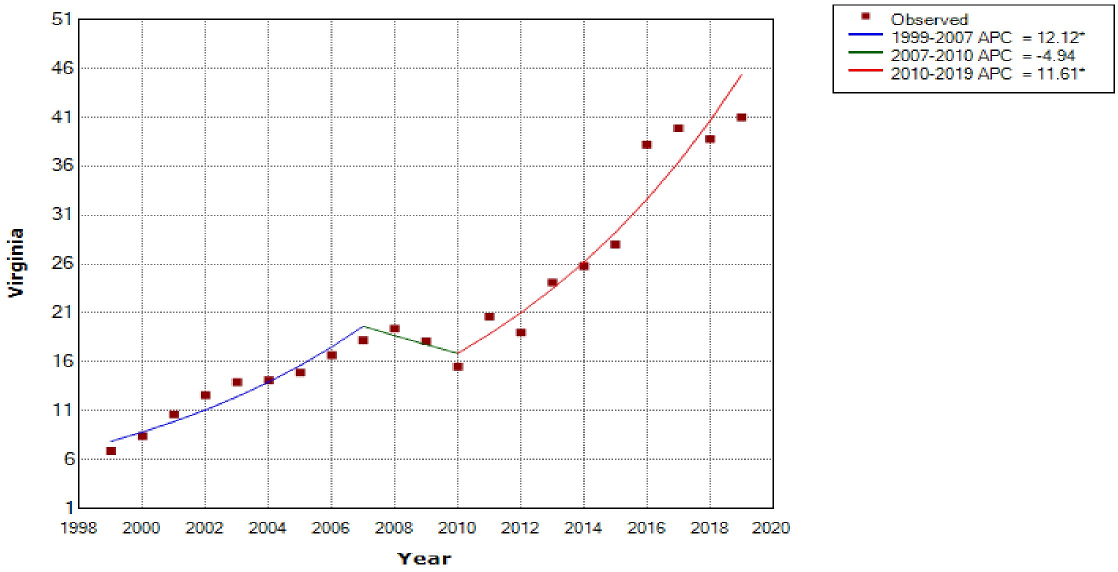
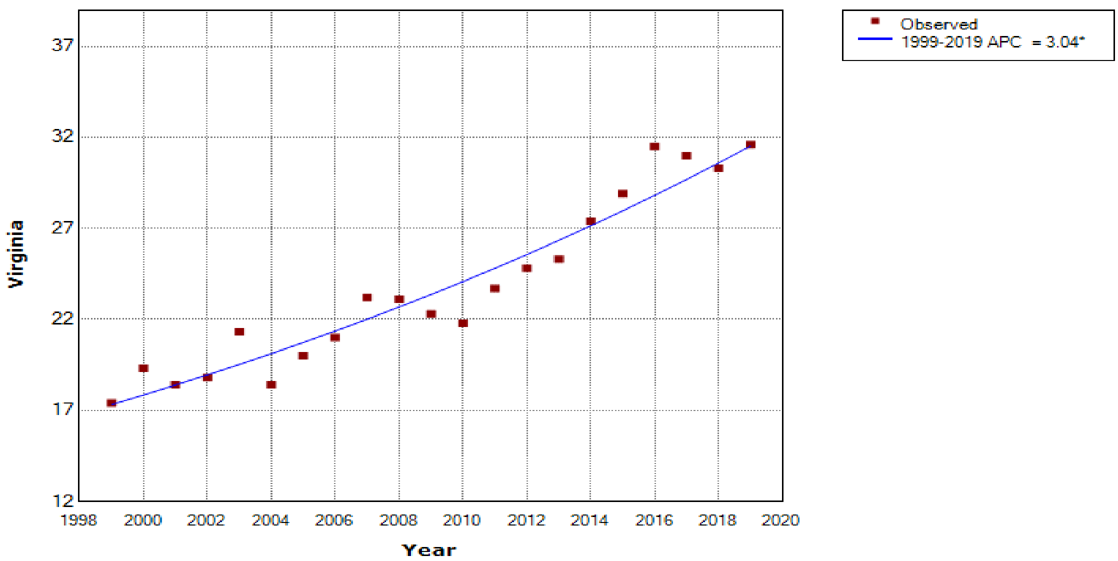


Figure 61. Trends of DoD in Virginia





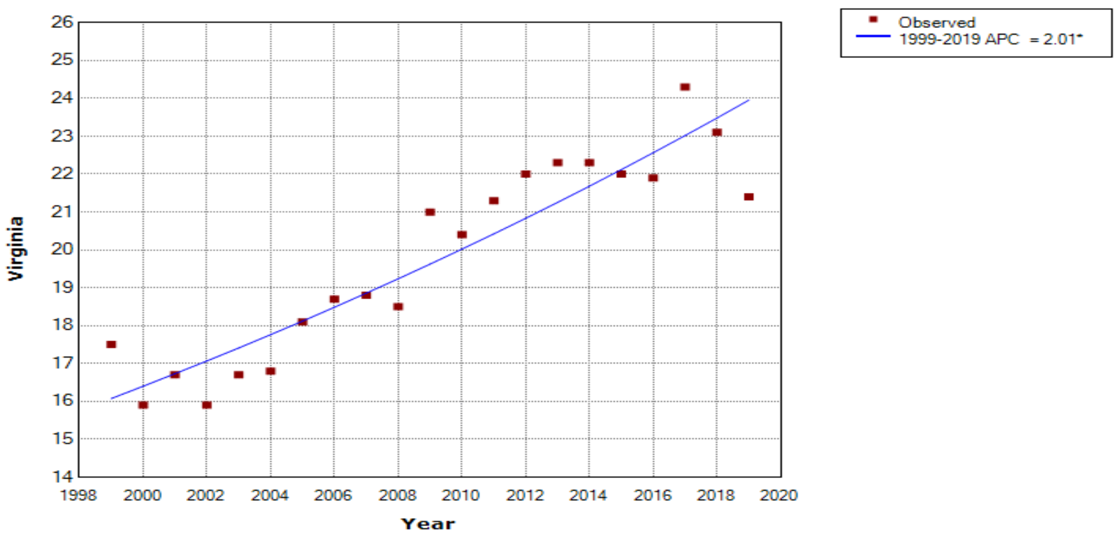


Figure 62. Trends of DoD in Washington

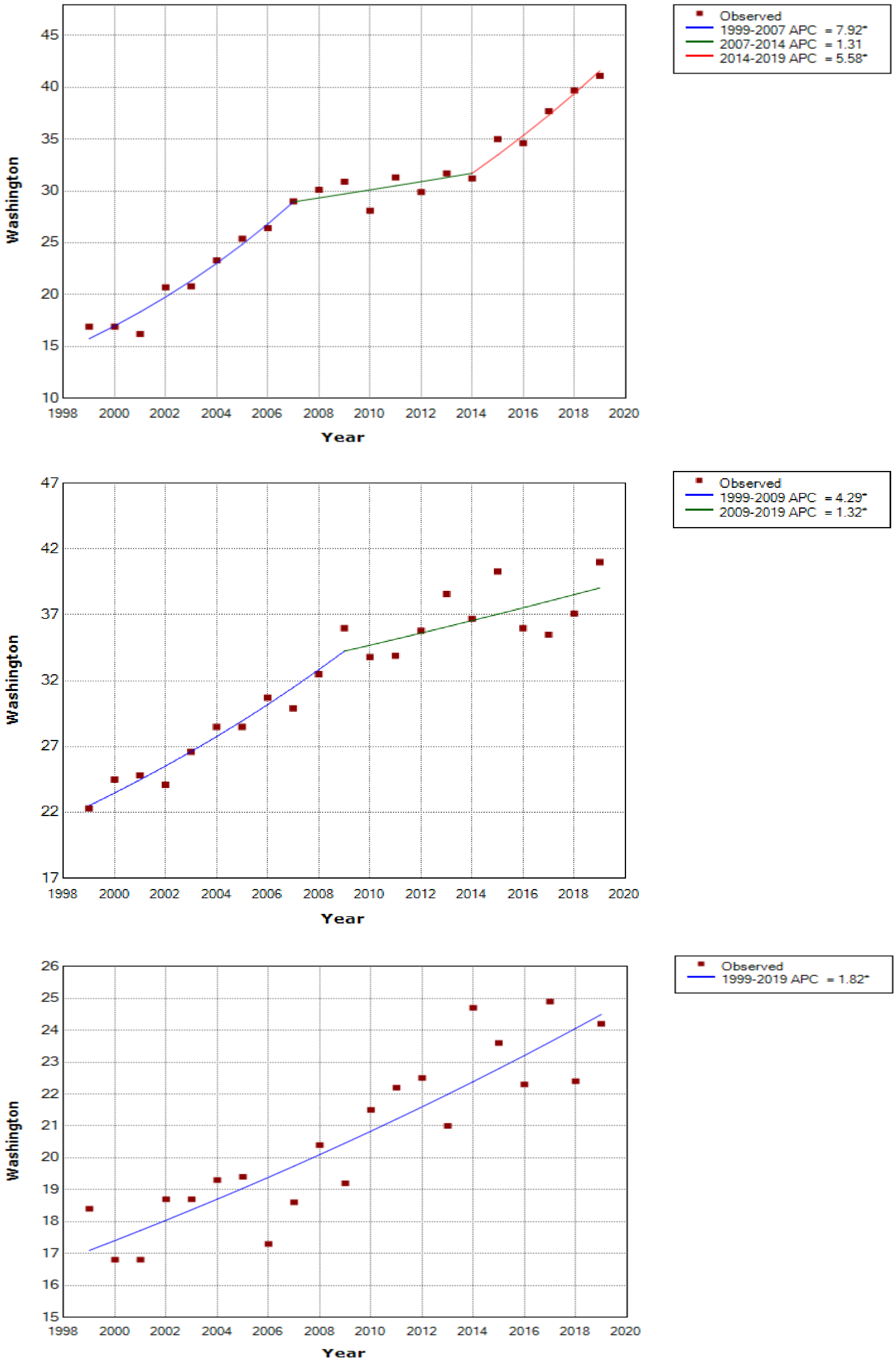


Figure 63. Trends of DoD in West Virginia

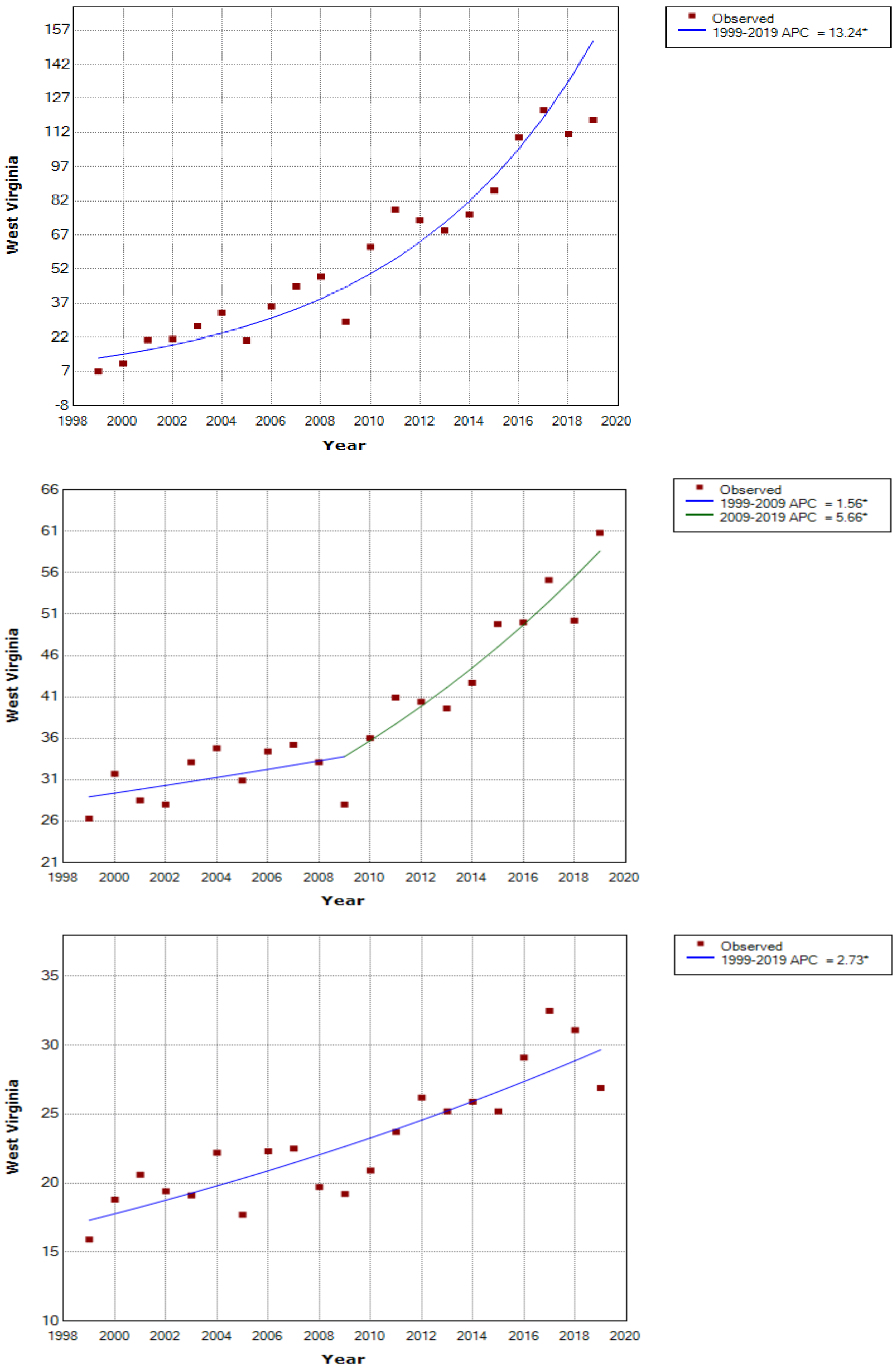


Figure 64. Trends of DoD in Wisconsin

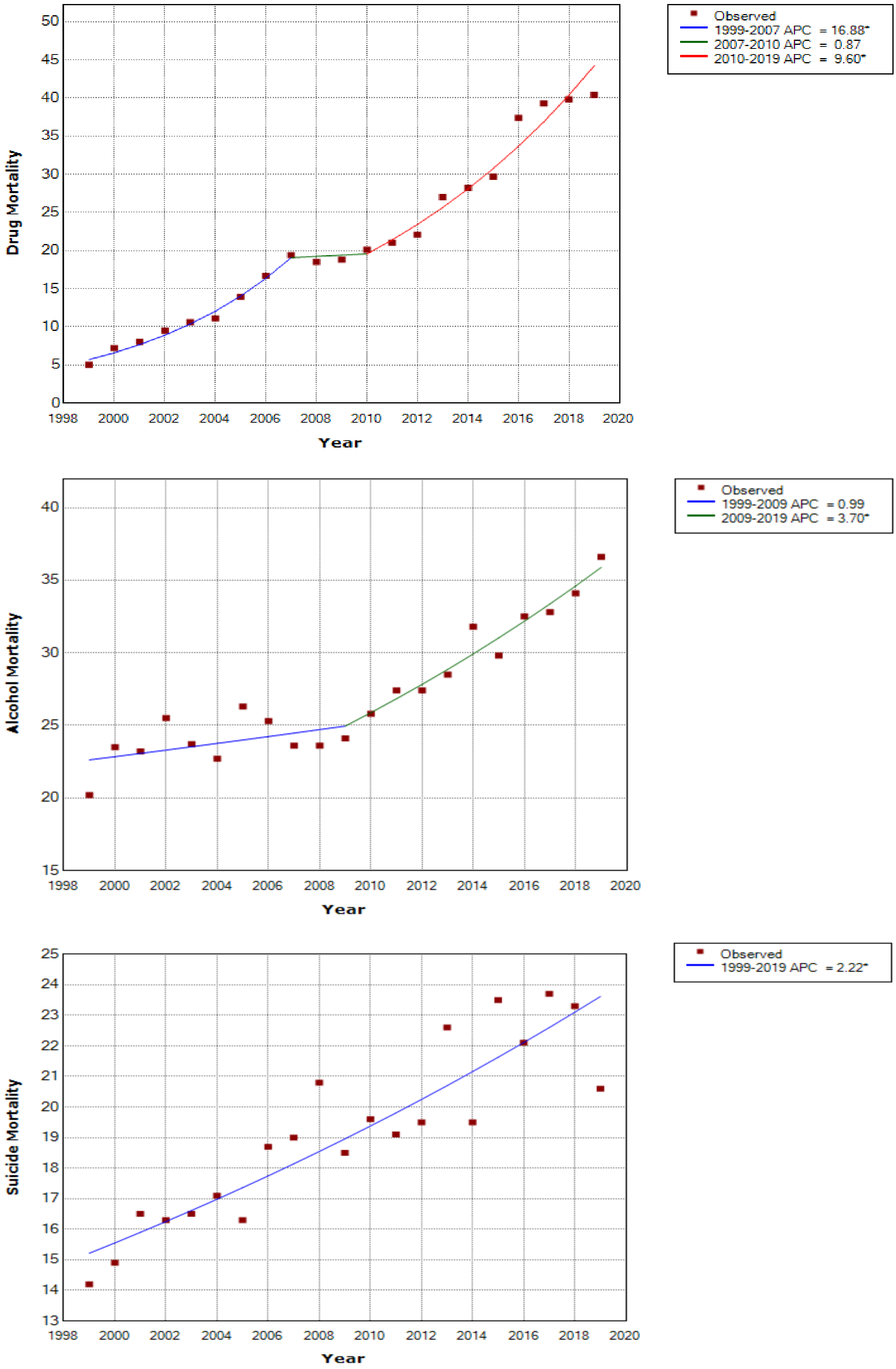
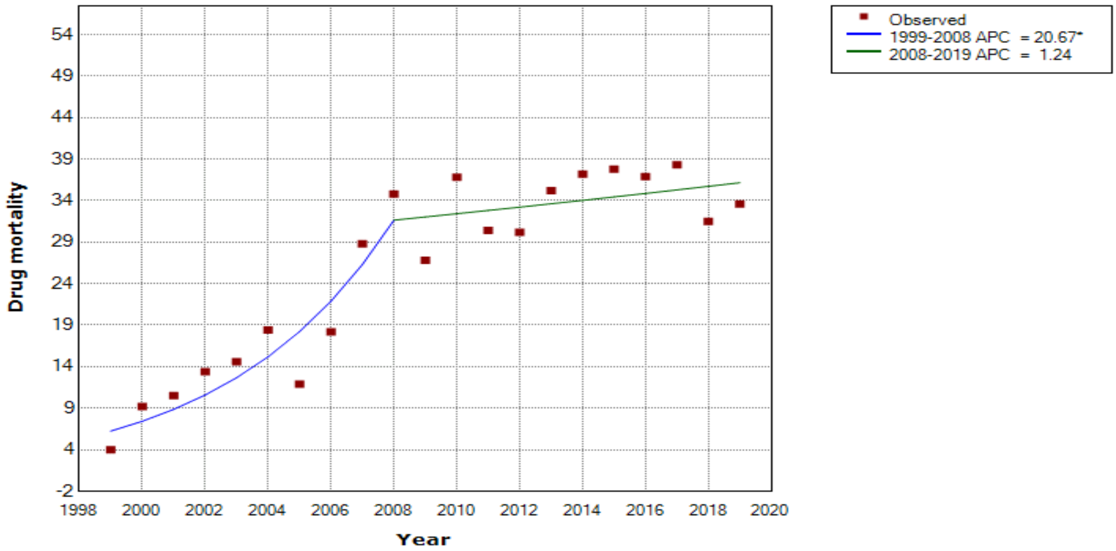
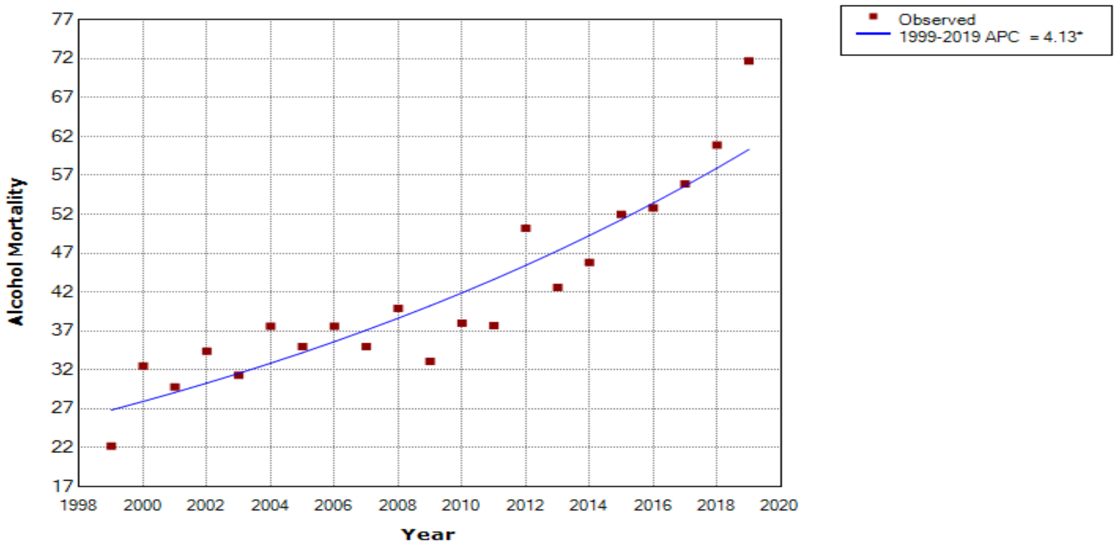
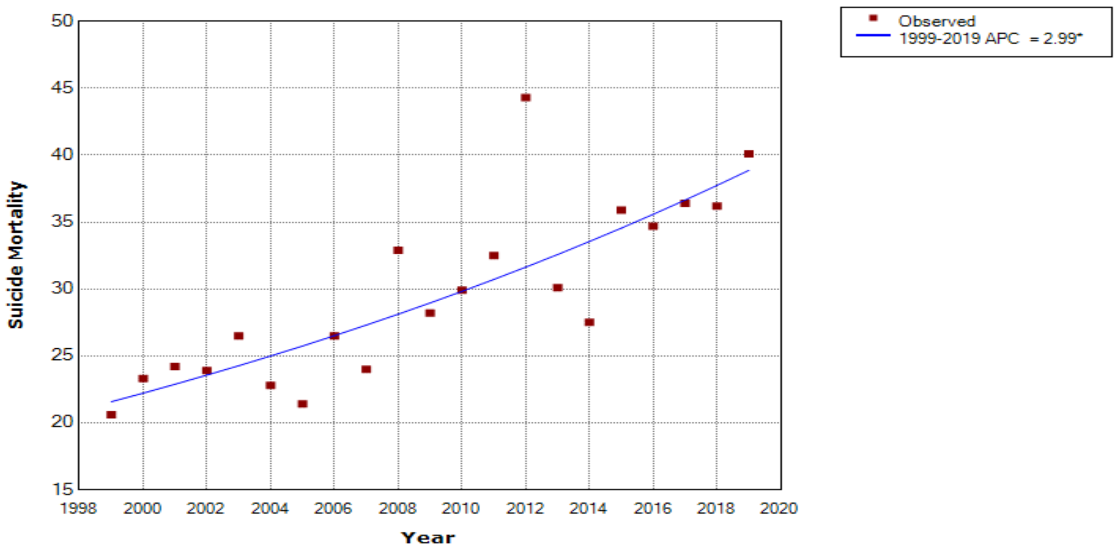


Figure 65. Trends of DoD in Wyoming







CURRICULUM VITAE

Amin Etemadifar

Utah State University, Department of Sociology, Social Work and Anthropology,

0730 Old Main Hill, Logan, Utah 84322-0730

Phone: (419)-450-2930 Email: amin.etemadifar@usu.edu

Education

2021 (Expected)	Ph.D. Sociology, Utah State University, Utah
2016	M.A. Sociology, University of Toledo, Ohio
2012	M.A. Political Science, University of Tehran, Iran
2006	B.S. Electrical Engineering, University of Kashan, Iran

Teaching and Research Interests

Statistics and Quantitative Methods, Sociology of Religion, Demography and Population, Population Health, Spatial Analysis, Ethnography

Recent Teaching and Research Experiences

Research Assistant, Utah State University, Department of Sociology, Fall 2017 – Spring 2021

Instructor, Course: Social Statistics, Utah State University, Summer 2019.

Instructor, Course: Social Problems, University of Toledo, Spring 2017.

Instructor, Course: Intro to Sociology, University of Toledo, Fall 2016.

Teaching Assistant, Courses: Sociology of Health and Medicine, Research Methods, University of Toledo, Spring 2015, Fall 2015, Spring 2016.

Honors and Awards:

Kim scholarship award ($6,388) , Yun Kim Population Research Lab, Utah State University (Fall 2018 and Spring 2019).

X-Stem fellowship ($12,000 per year), From State of Utah (2017 to 2020).

Top graduate student award, Tehran University (2012).

Computer Skills

SPSS, SAS, Stata, R, ArcGIS, EndNote, Microsoft Office (Word, Excel, PowerPoint), Qualtrix.

Peer-Reviewed Publications

Etemadifar, Amin, Eric Reither, and Tom Muller. (Forthcoming). "***A Socio-Spatial Analysis of Deaths of Despair."***

Etemadifar, Amin, and Eric Reither. (Forthcoming). *"Trend analysis of Deaths of Despair in the US,"*

Sung, Baksun, and Amin Etemadifar. 2019. *"Multilevel Analysis of Socio-Demographic Disparities in Adulthood Obesity Across the United States Geographic Regions,"* Osong Public Health Res, 10(3):137–144.

Etemadifar, Amin, and Ahmad Movassaghi. 2015. "Political Islam in Iran and Turkey." *Historical Studies of Islamic World.* 2(4):7-33.

Movassaghi, Ahmad and Amin Etemadifar. 2014. "Social Roots of Islamism in Iran and Post-Islamism in Turky." *Political Studies of Islamic World.* 3(9):157-181.

Recent Conferance Presentations

Etemadifar, Amin. 2021. "***Drug Deaths in the United States: A Socio-Spatial Analysis,"*** Paper Presented at Pacific Sociological Association Conference, March 17.

Etemadifar, Amin. 2018, "*A Spatial Analysis of "Deaths of Despair*," Paper Presented at Annual Utah Demography Summit. Oct. 26, Salt Lake City, UT.

Etemadifar, Amin. 2016. "*A Cross-National Comparative Analysis of Terrorism Based on the Theory of Anomie*." Paper Presented at 2016 Annual Meeting of Society for the study of Social Problems. August 19. Seatle, WA.

Etemadifar. Amin. 2016. "*Chaos Theory and the Middle East."* Paper Presented at Midwest Graduate Research Symposium. April 9. Toledo. OH.

Etemadifar, Amin. 2016. "*Inequality and Anomie: A Cross-Country Comparative Stud*y." Paper Presented at Society 2016 Annual Meeting of Mid-West Sociological Society. March 24. Chicago, IL.

Professional Memberships

American Sociological Association

The Pacific Sociological Association

Population Association of America